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A DYNAMIC STOCHASTIC MODEL OF MEDICAL CARE USE AND WORK ABSENCE

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This research explores the medical care consumption and absenteeism decisions of employed individuals with acute illnesses in an effort to better understand behavior that may contribute to the upward spiraling costs of health care. The theoretical framework models the decisions to visit a doctor and/or to miss work during an episode of acute illness as the sequential choices of individuals solving a discrete choice stochastic dynamic programming problem. Using data from the 1987 National Medical Expenditure Survey (NMES), I estimate the structural parameters of an individual's optimization problem. Structural estimation, as opposed to conventional reduced form estimation methods that are prevalent in the health care literature, allows for the introduction and evaluation of the impact of new public policy initiatives relating to health care. The estimates allow for predictions of the change in physician services use and illness-related absenteeism that arise with improvements in access to health care through more complete health insurance and sick leave coverage.

KEYWORDS: Medical care use, absenteeism, dynamic programming, health insurance.

1. INTRODUCTION

MEDICAL CARE VOLUME AND INTENSITY growth (increases in the number and types of services being consumed) accounted for 41.2% of the increase in expenditures for physician services between 1985 and 1990 (Sonnefeld et al. (1991)). Suggested as one explanation for the increase in medical care use is the growing prevalence of third party payers which has driven the price of medical care close to zero for many consumers. In fact, out-of-pocket payment percentages (that percent of total medical care costs for which consumers are responsible) fell from 62.7% in 1960 to 18.7% in 1990 (Levit et al. (1991)). Consequently, insured consumers use more medical care services in the event of illness than those facing the full market price of health care.[2] Another important societal cost of illness is the loss of output associated with illness-related employee absences: almost 2% of the scheduled work time of U.S. workers is lost due to illness (Vistnes (1997)). Despite their costs, medical care consumption and absenteeism may benefit an ill individual by reducing the length of the illness episode. It follows that health insurance and sick leave policies may have

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[2] In addition to moral hazard, physician inducement may account for some of the increase in volume and intensity. Several papers have been written on the subject with initial interest generated by Evans (1974).

significant effects on the medical treatment and work loss decisions of individuals during an episode of illness.

Most empirical analyses of the demand for medical care are only loosely based on extensions to Grossman's (1972) theoretical lifetime utility maximization model, where medical care is an input to the health production function and health is both a consumption good and an investment good. Instead, many empirical studies are motivated by the statistical methods promoted in the widely cited Rand Study.[3] These "two- and four-part models," as they have been termed in the literature, typically consist of a probit equation for the probability that a person has any medical expenditures during the year (or multiple equations differentiating types of medical services) and linear equation(s) for log annual expenditures conditional on any expenditures.[4] However, individuals do not determine at one time the number of provider visits they will have over a year or even over an episode of treatment (which is defined by the utilization of medical care as opposed to the onset of and recovery from illness). Rather, decisions to consume medical services are sequential and contingent: decisions today depend on what happened yesterday and what is expected to happen tomorrow. Thus, a more complete analysis involves understanding the daily behavior associated with contraction of illness, medical care utilization, and recovery from illness. Existing empirical models of medical care demand ignore these dynamic, and possibly endogenous, transitions.[5]

Three deficiencies in the empirical demand for health care literature include: the failure to adequately model behavior that determines zero expenditures and the subsequent correlation between the participation and expenditure equations, the casual use of theory to support the statistical equations, and the restricted use of annual data to explain behavioral decisions that occur within the year. The 1987 National Medical Expenditure Survey (NMES) disaggregates medical care use beyond annual counts or episodes of treatment and allows for the modeling of an individual's daily behavior from the onset of an illness and over the entire illness episode. The survey provides the most current and most disaggregated data for capturing specific illness information and daily decisions during an illness. By using these data to estimate the structural parameters of a dynamic stochastic discrete choice model of medical care utilization, I explicitly address the three limitations mentioned above.

[3] In 1974 the federal government commissioned an experiment where consenting individuals were randomly assigned health insurance plans and their medical care consumption behaviors were recorded over a three to five year period. See Newhouse (1993) for a complete summary of the experiment and subsequent research.

[4] For specific papers, see Duan et al. (1983, 1984), Manning et al. (1987), Keeler, Manning, and Wells (1988), and Cameron et al. (1988), among others.

[5] Dardanoni and Wagstaff (1990) demonstrate that uncertainty of illness plays an important part in their theoretical model of medical care demand. They explicitly model uncertainty pertaining to incidence of illness and effectiveness of medical treatment. Empirical studies of medical care demand often abstract from these issues because most health surveys fail to document illness contraction and recovery.

Because absenteeism may be an important substitute for or complement to medical care use, I also model decisions to miss work during an illness. Much of the literature that combines health and its effects on the worker seeks to explain labor force participation rather than short-run changes in the supply of labor. Acute conditions, as opposed to chronic illnesses or chronic health problems, are most likely to affect the daily work experience of individuals.[6] Because this paper examines individual behavior during an episode of acute illness, it focuses on how illness affects the absence behavior of employed individuals rather than how illness affects labor force participation.

Because it is difficult to accurately account for all influences on the demand for medical care (e.g., contraction of illness, severity of illness, physician inducement, the variety of treatment alternatives, treatment effectiveness, health insurance alternatives, numerous insurance characteristics, and household consumption of medical care), modeling the behavior of health care consumers (and potential consumers) is, admittedly, a challenge. My research addresses some of these aspects of health care demand with an approach that combines the economic and biological behavior described by the theoretical model with empirical analysis of the data. While the focus of the paper is on behavior over an acute illness episode, the application of this modeling and estimation approach to the demand for medical care can lead to larger, more encompassing models of health care behavior.

More specifically, I model the decisions to seek medical treatment and to miss work during an episode of acute illness as the sequential choices of employed individuals solving a discrete choice stochastic dynamic programming problem.[7] At each discrete period of an illness the forward-looking individual chooses whether or not to seek medical treatment and whether or not to miss work based on expected utility maximization. Allowing for uncertainty, decisions made at each period depend on the stochastic event of illness and the effectiveness of medical treatment and work absence in shortening the length of the illness episode. The structural parameters of the daily optimization problem are estimated using data from the 1987 NMES.

Although burdened by computational complexity, estimation of structural parameters using a dynamic programming solution framework has gained widespread appeal and has been applied in many areas: labor force participation, fertility and child mortality, job matching and occupational choice, patent renewal, and engine replacement, for example.[8] A theoretical model based on this framework was introduced to the health care literature twenty years ago

[6] Economic studies of the short-run responses to health problems include the work of Allen (1981), Paringer (1983), Barmby and Treble (1994), and Vistnes (1997).

[7] Eckstein and Wolpin (1989a) and Rust (1994) provide excellent surveys of the methods for solving and estimating discrete stochastic dynamic programming models.

[8] See Wolpin (1984, 1992), Miller (1984), Pakes (1986), Rust (1987), Eckstein and Wolpin (1989b), Berkovec and Stern (1991), Rust and Phelan (1997), and Keane and Wolpin (1997).

(Keeler, Newhouse, and Phelps (1977)), but, surprisingly, no one has pursued estimation of such a model of medical care utilization.[9] In addition to filling this void in the empirical demand for medical care literature, my paper makes several contributions regarding the empirical methodology. (i) It allows for analysis of the day by day dynamics of illness, medical care consumption, and absenteeism by using detailed information available only in the NMES data. (ii) It introduces a stationary "well value function" that allows for the nesting of a dynamic programming model of daily decisions during an illness episode within a larger infinite horizon model, avoiding the need to solve a daily optimization problem over an individual's remaining lifetime. (iii) It demonstrates how the explicit modeling of biological and economic behavior can be used to derive the probabilities that define the censored likelihood function resulting from data collection methods in the NMES.

The determination of policy-invariant structural parameters allows for the introduction and evaluation of different policies that affect the financial constraints of a consumer's decision-making problem. The policy instruments in the paper involve health insurance, sick leave coverage, and access to medical care. I find that a larger percentage of individuals rely on work absence for recovery from an acute illness than on medical care and advice from a physician (77% vs. 47%). Policy experiments reveal changes in treatment behavior by as much as 63% under some alternatives. Depending on the type of illness, absence behavior changes by as much as 66%. Medical care visits and illness-related absences appear to be complements among some groups of individuals and substitutes among others. The introduction of alternative policies tends to have little effect on the average duration of the illnesses, but does produce substantial variation in utilization of medical care and absenteeism across different income, health status, age, sick leave, and health insurance groups.

I describe the data and sample selection criteria in the beginning of Section 2 and conclude the section with descriptive statistics associated with my sample. I present the theoretical model of dynamic sequential decisions with regard to medical treatment and work absence in Section 3 and discuss empirical implementation of the model in Section 4. The estimation results are presented in Section 5 with intuitive, graphical, and statistical interpretation of the model's fit. Section 6 describes and evaluates various public policy experiments. I also compare the estimation results from the behavioral model to those from two statistical reduced form approaches. Section 7 concludes. Solution of the optimization problem and construction of the appropriate likelihood function are described in detail in the Appendices.

[9] The empirical analyses based on the dynamic theoretical model described by Keeler, Newhouse, and Phelps (1977) (their own, Ellis (1986), and Ellis and McGuire (1986)) reduce to the familiar two-part model used extensively in the health care literature.

2. DATA DESCRIPTION

2.1. *Description of the Survey*

The 1987 National Medical Expenditure Survey is a national probability sample of the civilian, noninstitutionalized population and contains detailed information on health status, medical care utilization, health insurance coverage, employment, sick leave, income, and demographics. It oversamples Blacks, Hispanics, and the poor to allow for more precise estimates of the medical care use and expenses for population subgroups that may be of particular policy interest.

Participants in the survey were asked to keep a daily log of their illness-related behavior over the 1987 calendar year. Interviewers visited participants three or four times during the year in order to record behavior up to that date and to verify previously obtained information. The logged behavior includes dates of all illness episodes, of all medical services use, and of all disability days.[10] However, the survey does not record episode information for illnesses in which the individual sought no medical treatment and reported no disability days. This censoring problem is explicitly accounted for in construction of the likelihood function which allows for identification and estimation of the daily illness probability parameters.

Separate questions are asked about each medical provider visit, including physician office visits, hospital emergency room visits, hospital outpatient visits, hospital inpatient stays, all other medical provider visits, and use of prescribed medicines.[11] Charges and sources of payment for each medical provider visit are provided. After receiving a bill or statement the person was asked the total charge for the visit, what portion of the bill he paid, and what portion was paid by other sources (e.g., private insurance, Medicaid, Medicare).

The survey includes the dates of all illness-related work-loss days during 1987. Because specific illness codes and episode lengths are associated with all recorded absences, these absences are not likely to be vacations or shopping days. That is, the usual concerns that self-reported absence data suffer from measurement error because employees are reluctant to report actual reasons for an absence are abated since detailed information about the illness that prompted the absence is also requested and recorded in the daily logs. Unfortunately, the

[10] The beginning date of an illness is defined by the first day that an individual began feeling ill or the first day that a medical provider discovered the illness. The day of full recovery or the day that a provider said the person was well defines the ending date of an illness. The illness conditions are classified according to the National Health Interview Survey modification of the International Classification of Diseases, Ninth Revision (U.S. DHHS (1980)). For many illnesses that were medically treated, the illness codes are available from the medical records of the individual. In cases where a diagnosis from a medical professional was unavailable, medical coders probed individuals about their symptoms to determine the appropriate code.

[11] I analyze physician visits only because modeling the choices among numerous medical care alternatives increases the complexity of the problem. Physician visits include visits to an office, an outpatient setting, or an emergency room.

survey reports only whether a person had paid time off if ill or paid medical leave to visit a doctor; questions about the stock of sick leave are not asked. Additionally, the data indicate some economic and demographic variables at each interview round (e.g., employment and marital status). Dates of these transitions, however, are not available. A health status questionnaire was administered in one round which provides overall health status information at one point in time. The usual demographic variables are available.

2.2. *Determination of the Sample*

The sample used to estimate the model of episodic behavior consists of males age 25 to 64 who reported being employed (but not self employed) during each of the interview rounds. The "full sample" consists of 3797 males and includes both ill and well individuals. Individuals from the full sample who are observed to have an episode of acute illness make up the "ill sample." Estimation results are based on all individuals from the full sample, regardless of whether or not they are observed to have an acute illness episode. The sample selection criteria are detailed in Table I.

The illnesses of individuals in the ill sample are acute conditions according to the International Classification of Diseases (ICD-9) and the condition code reported in the NMES data. The acute conditions considered are infectious and parasitic diseases and respiratory conditions which include, for example, strep throat, viral infection, influenza, and the common cold. These acute conditions account for almost 60% of all acute conditions (Adams and Benson (1992)).[12] Because the computational complexity associated with solving the dynamic programming problem depends on the length of the decision-making behavior, the ill sample excludes individuals with episodes that number 22 or more days.[13]

[12] In order to understand treatment and absence behavior over an episode of illness, as well as the transitions into and out of illness, I restrict attention to a specific class of illness. Three considerations influenced this decision. As stated by Brown and Sessions (1996, p. 42), "in order to analyse the unexpected behaviour of workers [...] attention should be drawn away from events which cause severe adverse health effects which may lead to long term or even permanent absence from work and towards the effects of day to day sickness." Evidence from Leigh (1989) indicates that acute illnesses such as colds and flu have the most influence on illness-related absenteeism. Secondly, the health status variable in the NMES data set is collected only once during the survey period. Thus, it is necessary that the illness not alter one's health status over time since changes in health are not observed. Lastly, acute conditions are characterized by a sudden onset, a sharp rise, and a short course. In contrast, chronic conditions are typically associated with a long duration or frequent recurrence over a long time (e.g., heart disease, migraine headaches) and, thus, have effects over one's lifetime.

[13] Many definitions of acute illnesses classify them as episodes lasting at most 90 days. Of all individuals in the data with acute illness episodes, 90.7% were well by the end of 21 days. Other than the expected differences in number of visits and absences per episode (those individuals with episodes longer than 21 days had, on average, 1.50 visits and 3.66 absences per episode compared to those in the subsample who averaged 1.13 visits and 1.91 absences per episode), the only noticeable demographic or economic difference consists of a two year increase in the age of the discarded sample over the selected sample. The differences in lengths of episodes are most likely associated with unobserved severity of illness.

TABLE I

SAMPLE SELECTION INFORMATION

Selection Criteria	Remaining Sample Size
NMES participants	38446
Aged 25–64 years	18059
and male	8325
and employed full time, full year	6630
and completed Health Status Questionnaire	5287
and no federal insurance assistance	5069
and valid responses for key variables	4608
and no illness and/or at least one acute illness ($\leq$ 90 days)	4608
and no illness and/or at least one acute illness ($\leq$ 21 days)	4513
and not self employed	3797

Of the 3797 males in the full sample, 726 males (19.1%) experience an acute infectious, parasitic, or respiratory illness episode lasting at most three weeks.[14] Figure 1 shows the distribution of episode lengths in days for individuals in the ill sample. The spike in the distribution at eight days may be associated with physician inducement. That is, the provider may ask the patient to return in one week for a follow-up examination. The doctor may then relay to the patient that he is well, marking the end of his illness episode. Figure 1 also depicts the recovery hazard for ill individuals. The recovery hazard measures the probability of recovery at the end of day t, conditional on being ill through day t. The hazard, unconditional on the medical treatment and work absence history of an individual, is increasing with the duration of illness, although not monotonically.

The proportion of individuals in the selected full sample (or in the entire data set for that matter) who report having an acute illness underpredicts the true probability of having an illness episode. Information about an illness episode, and even whether an individual was ill or not, is not recorded in the publicly available NMES data unless the individual sought treatment or missed work at least once during the illness episode. Thus, users of these data (and many other health data sets) do not observe all illnesses over the survey period. Appendix B discusses this censoring problem further and details correction of the likelihood function.

2.3. *Categorization of Individual Types*

Individuals from different demographic and economic backgrounds may exhibit different behavior with regard to contraction of illness, recovery from illness, medical care utilization, and absenteeism. Solution of the dynamic

[14] The U.S. National Center for Health Statistics (1989) reports that infectious and parasitic diseases have an annual incidence rate of 18.3 per 100 males and that respiratory conditions occur at a rate of 35.6 (upper respiratory) and 53.9 (other respiratory) per 100 males. The frequencies per 100 individuals by age are 13.5, 33.2, and 56.5 for individuals aged 25 to 44 and 8.6, 21.4, and 38.6 for those aged 45 to 64, for the three illness classifications listed above.

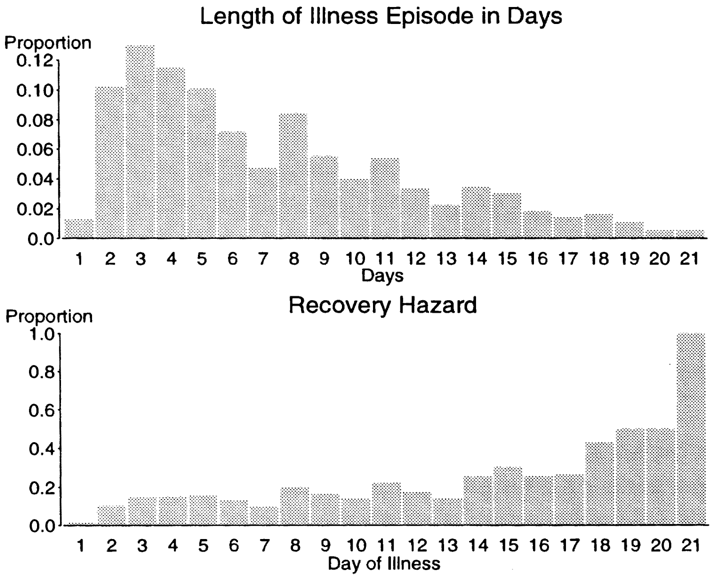


FIGURE 1.—Characteristics of illness episodes.

programming problem is necessary for each unique combination of characteristics describing individuals. Thus, some measures of the observed heterogeneity of individuals are divided into discrete classes, rather than assuming a continuous outcome that would require solution of the dynamic programming problem for each individual in the full sample. The variables used to classify individuals into unique "types" are daily income, sick leave availability, health insurance coverage, health status, and age.

Daily income consists of three classes: lower income, middle income, and upper income. A daily wage of less than \$70 (\$17,500 per year) defines the lower-income interval. Middle income consists of wages between \$70 and \$125 per day (\$31,250 per year). Upper-income individuals have wages greater than or equal to \$125 per day. The median daily wages within each income classification are \$48.00, \$96.00, and \$168.00.

Sick leave availability also characterizes the sample. Although information on the stock of sick leave is unavailable, the data do indicate whether an individual has paid sick leave or not. Section 3 describes my efforts to model the costs of depleting one's stock of sick leave.

Health insurance coverage, or more specifically, the percent of the total medical care charge for which a person is responsible, varies across people and affects the decision problem through the budget constraint. If an individual seeks treatment, then the total price of treatment and the amount paid out-of-pocket by the individual are available. For an individual who never sought treatment from a physician for an acute illness (either because he was ill but chose not to seek treatment or because he was not ill), information on the percent of the total bill for which he would be responsible is not available. The survey does report, however, whether the individual has health insurance or not.[15] For an individual who seeks treatment and is insured, I use the out-of-pocket percentage for which he is responsible (determined as the average percent paid out of pocket over the illness episode) to describe different classes of responsibility. The discrete classifications are 0%, 20%, and 100%, where anyone paying less than 10% out of pocket is assigned 0% and anyone paying over 90% out of pocket is assigned 100%. Twenty percent represents the median out-of-pocket percentage paid by the remaining insured individuals who sought treatment during the illness episode. The uninsured, a fourth class of insurance, pay 100% of the total charge for medical care.

Demographic variables that might describe one's type include health status, age, race, education, and marital status. The only variables included in the estimated specification are health status and age.[16] The data include a self-reported health status for each individual as excellent, good, fair, or poor. Because only a small number of individuals report a poor health status, I group fair and poor health statuses together. Two age classes are considered: 25–44 years and 45–64 years.

Table II describes the ill and full sample by observed characteristics. Some important differences exist between the full sample and the ill sample. In general, individuals who experience an acute illness and choose to visit a physician or to be absent from work at least once during the illness episode appear to be insured and to be younger. They also have higher incomes and have sick leave coverage.

2.4. *Discussion of Data Observations*

Tables III through VI contain additional information about the sample. It is apparent (Table III) that the percent of persons in fair or poor health is largest among lower-income males (13%) and decreases as income rises (11% and 6% for middle-income and upper-income males, respectively). Similarly, the percent of lower-income males reporting an excellent health status (25%) is much smaller than that of the middle- and upper-income groups (33% and 38%). Individuals with lower incomes tend to be younger (85%), while a higher percentage of older individuals (39%) report having higher incomes. Older individuals also appear to have lower health status; 16% of older males report a fair or poor health status and only 9% of younger males do.

[15] The likelihood function accounts for unobserved data on the out-of-pocket responsibility of insured individuals who do not seek treatment when ill or who are not observed to be ill. Appendix B explains this feature of the likelihood function in much detail.

[16] Although I recognize that other characteristics may potentially affect an individual's optimization problem, I limit the observed heterogeneity of individuals to daily income, sick leave availability, health insurance coverage, health status, and age in order to reduce computational complexity. The effects of this restriction are discussed in Sections 5 and 6.

TABLE II

PROPORTIONS AND MOMENTS OF THE ILL AND FULL SAMPLE

Characteristic	Ill Sample (726) Prop.	Median	Mean	St. Dev	Full Sample (3797) Prop.	Median	Mean	St. Dev
Daily Income								
Lower	0.30	52	49.89	15.45	0.35	48	47.24	15.79
Middle	0.42	98	96.96	15.62	0.40	96	95.51	15.53
Upper	0.28	160	185.78	78.04	0.25	168	185.85	88.29
Sick Leave								
Available	0.74				0.68			
Not Available	0.26				0.32			
Health Insurance								
Uninsured	0.07				0.12			
Insured	0.93				0.88			
Health Status								
Excellent	0.32				0.33			
Good	0.58				0.55			
Fair/Poor	0.10				0.12			
Age								
25–44 Years	0.77	33	33.62	5.37	0.69	34	33.82	5.56
45–64 Years	0.23	52	52.99	5.37	0.31	52	52.87	5.64

Note: Prop. measures the proportion of the ill sample (full sample) in each group.

Table IV displays the prevalence of sick leave and health insurance coverage by observed characteristics. While nearly all upper-income individuals have sick leave provisions through their employer (87%), less than half of the lower-income individuals have sick leave coverage. Although the data do not provide out-of-pocket percentages for individuals who do not visit a physician during an illness, the survey does report whether or not an individual is insured. Almost all of the upper-income males in the ill sample report being insured (99%), but

TABLE III

CHARACTERISTICS OF THE ILL SAMPLE BY INCOME, HEALTH STATUS, AND AGE

	By Characteristic							
	Income			Health Status			Age	
Distribution of	Lower	Middle	Upper	Excellent	Good	Fair/Poor	25–44 Yrs.	45–64 Yrs.
Daily Income								
Lower	1.00	0.00	0.00	0.25	0.62	0.13	0.85	0.15
Middle	0.00	1.00	0.00	0.33	0.56	0.11	0.78	0.22
Upper	0.00	0.00	1.00	0.38	0.56	0.06	0.68	0.32
Health Status								
Excellent	0.23	0.44	0.33	1.00	0.00	0.00	0.81	0.19
Good	0.32	0.41	0.27	0.00	1.00	0.00	0.77	0.23
Fair/Poor	0.39	0.46	0.15	0.00	0.00	1.00	0.65	0.35
Age								
25–44 Yrs	0.33	0.43	0.24	0.33	0.58	0.09	1.00	0.00
45–64 Yrs	0.20	0.41	0.39	0.27	0.57	0.16	0.00	1.00

TABLE IV

INSURANCE STATUS BY CHARACTERISTIC

Characteristic	Sick Leave No	Sick Leave Yes	Health Insurance No	Health Insurance Yes	Out-of-Pocket Responsibility of the Insured < 10%	10–90%	> 90%	SS
Health Insurance								
Uninsured	0.76	0.24	1.00	0.00	—	—	—	0
Insured	0.27	0.73	0.00	1.00	0.30	0.25	0.45	272
Daily Income								
Lower	0.52	0.48	0.26	0.74	0.28	0.21	0.51	68
Middle	0.26	0.74	0.05	0.95	0.29	0.29	0.42	119
Upper	0.13	0.87	0.01	0.99	0.34	0.21	0.45	85
Sick Leave								
Available	0.00	1.00	0.04	0.96	0.31	0.25	0.44	203
Not Available	1.00	0.00	0.27	0.73	0.29	0.25	0.46	69
Health Status								
Excellent	0.26	0.74	0.10	0.90	0.29	0.29	0.42	80
Good	0.34	0.66	0.11	0.89	0.29	0.25	0.46	162
Fair/Poor	0.42	0.58	0.17	0.82	0.43	0.13	0.43	30
Age								
25–44 Years	0.34	0.66	0.14	0.86	0.31	0.22	0.47	194
45–64 Years	0.28	0.72	0.07	0.93	0.30	0.32	0.38	78

Note: Only individuals in each group who experience at least one nonzero charge for medical care and who are insured (SS) are used in calculation of the out-of-pocket responsibility proportions. All numbers in the table are proportions, except SS.

TABLE V

TREATMENT, ABSENCE, AND EPISODE LENGTH AVERAGES BY CHARACTERISTIC

Characteristic	Prop.	Treatment $E(v)$	$E(v \mid v > 0)$	Absence $E(a)$	$E(a \mid a > 0)$	Episode Length $E(T)$	$E(T \mid v > 0)$	$E(T \mid a > 0)$
Daily Income								
Lower	0.16	0.47	1.06	1.48	2.00	7.30	9.77	6.34
Middle	0.20	0.49	1.16	1.43	1.87	7.34	10.45	6.38
Upper	0.22	0.53	1.14	1.31	1.86	7.44	9.66	6.42
Sick Leave								
Available	0.21	0.47	1.11	1.40	1.87	7.33	10.03	6.33
Not Available	0.16	0.56	1.18	1.44	2.01	7.43	9.98	6.51
Health Insurance								
Uninsured	0.12	0.61	1.07	1.29	1.89	7.55	9.45	6.66
Insured	0.20	0.49	1.13	1.42	1.91	7.34	10.07	6.36
Health Status								
Excellent	0.18	0.44	1.12	1.24	1.65	7.29	9.87	6.37
Good	0.20	0.53	1.13	1.39	1.93	7.35	9.98	6.20
Fair/Poor	0.17	0.47	1.09	2.05	2.49	7.57	10.62	7.26
Age								
25–44 Years	0.21	0.47	1.11	1.39	1.83	7.01	9.74	6.00
45–64 Years	0.14	0.59	1.16	1.49	2.17	8.52	10.75	7.77
Totals	0.19	0.49	1.13	1.41	1.91	7.35	10.01	6.38

Note: $E(\cdot)$ denotes expectation or average; v, a, and T denote visits, absences, and episode length. All averages are conditional on being observed to be ill. Prop. measures the proportion of individuals defined by each characteristic who are observed to be ill.

TABLE VI

NUMBER OF PHYSICIAN VISITS AND WORK ABSENCES

Ill Sample, $n = 726$

Number of Visits	Number of Absences 0	1	2	3+	Total
0	0.000	0.340	0.149	0.072	0.561
1	0.242	0.048	0.050	0.058	0.398
2	0.014	0.004	0.004	0.010	0.032
3+	0.003	0.000	0.000	0.007	0.010
Total	0.259	0.393	0.202	0.146	1.000

Ill Sample, episode ≤ 7 days, $n = 419$

Number of Visits	Number of Absences 0	1	2	3+	Total
0	0.000	0.475	0.205	0.074	0.754
1	0.122	0.065	0.038	0.031	0.227
2	0.010	0.002	0.002	0.002	0.017
3+	0.000	0.000	0.000	0.002	0.002
Total	0.131	0.513	0.246	0.110	1.000

Ill Sample, episode > 7 days, $n = 307$

Number of Visits	Number of Absences 0	1	2	3+	Total
0	0.000	0.156	0.072	0.068	0.296
1	0.407	0.065	0.065	0.094	0.632
2	0.020	0.007	0.007	0.020	0.052
3+	0.007	0.000	0.000	0.013	0.020
Total	0.433	0.228	0.143	0.195	1.000

26% of the lower-income males are uninsured. The average proportion paid out-of-pocket is available for individuals in the ill sample who visited a physician at least once during the year. A larger proportion of upper-income individuals report paying less than 10% of their medical charges (34%) compared to those with lower incomes (28%). Those individuals with higher incomes, however, are more likely to be insured which may induce them to visit the doctor more often than those who do not have health insurance (predominantly lower-income persons). As a consequence upper-income individuals may have exceeded the deductible limit and insurance may be paying a fixed proportion of their medical care costs.

Table V reports the average number of physician visits and work absences for different groups in the ill sample. I report the numbers for all individuals in the ill sample (i.e., $E(\cdot)$) and for those who had at least one of the events in question (i.e., $E(\cdot|\cdot > 0)$). Table VI lists the proportion of individuals in the ill sample who have a specific number of physician visits in combination with a specific number of work absences. The table also displays the marginal probabilities of the total

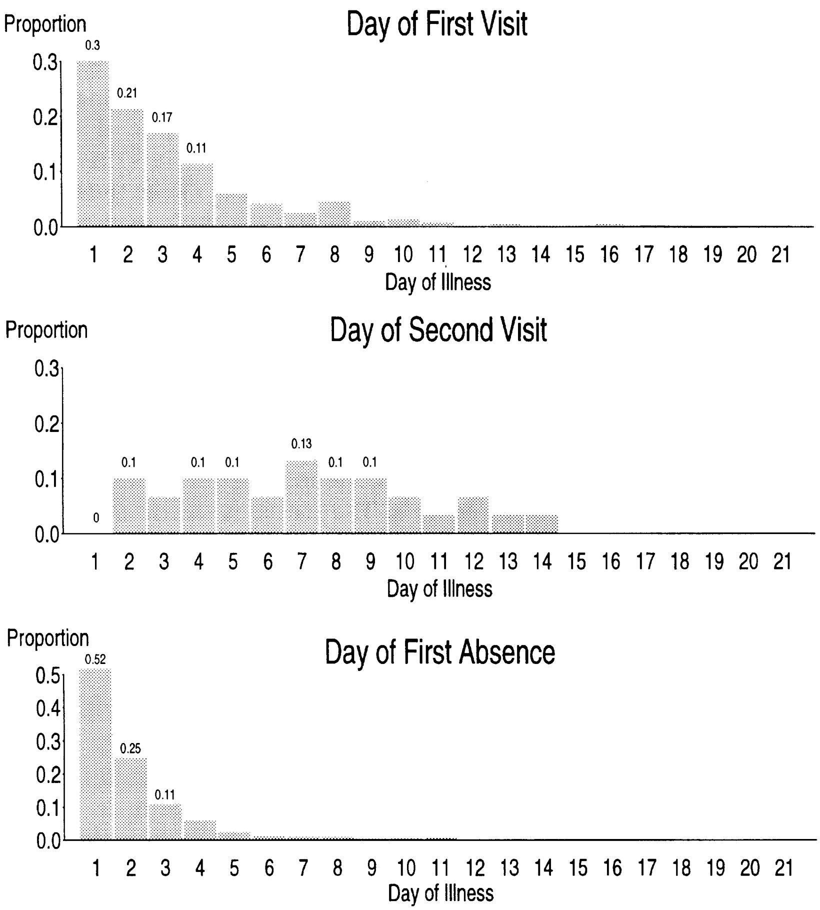


FIGURE 2.—Timing of visits and absences.

number of physician visits and illness-related work absences. When disaggregated by length of episode, it appears that a larger number of medical treatment visits is associated with illness episodes of a longer duration. Any absences appear to be relatively more likely in shorter episodes, but longer spells of absence are associated with longer illness episodes.

Finally, the timing of visits and absences is depicted in Figure 2. The first physician visit occurs on the first day of the illness in 30% of the episodes. Second visits of individuals who have more than one visit are most likely to be on the seventh day of an episode. Over half of all absence spells begin on the first day of an illness.[17]

[17] Only about 4% of the ill sample have more than one absence spell during an episode, where a spell is defined by continuous absence from work.

3. THE THEORETICAL MODEL

This section describes a dynamic stochastic model of medical treatment and work absence decisions that captures the sequential decision-making behavior of employed individuals with acute illnesses. At each discrete period an individual faces a time-invariant probability of contracting an acute illness that depends on exogenous demographic and health-related variables. Given income, health insurance, and sick leave coverage, an individual decides, upon becoming ill, whether or not to seek medical treatment and whether or not to be absent from work. By seeking treatment or by staying home from work, the individual may improve his chances of recovery. If treatment is sought, then the individual must incur the costs of treatment not covered by health insurance. Staying home from work implies that income may be foregone depending on the employer's sick leave provisions. Each period the individual may recover or remain ill, with the probability of recovery dependent on his history of medical treatment and work absence within the illness episode. The decisionmaking continues, with the same alternatives, until the individual recovers. The model is restricted to individuals who are employed. Because the choice of employer is not modeled, health insurance and sick leave coverage held by an employee are assumed exogenous.

3.1. *Per-period Discrete Choices*

Individuals in the model occupy one of $K+1$ distinct health states: well ($k=0$) or sick with an acute illness of type k ($k=1,\ldots,K$). I introduce unobserved differences in illness in order to distinguish between illnesses that may be differently affected by medical treatment and recuperation at home.[18]

An individual receives the utility associated with being well until contracting an illness of a specific type. Once ill, the individual makes optimizing decisions about medical treatment and work absence. The analysis ignores preventive treatment, so employed individuals who are free from illness have no medical visits and no illness-related absences. The alternatives available to an employed individual who is ill are:

$j=1$: work and do not seek treatment;

$j=2$: work and seek treatment;

$j=3$: do not work and do not seek treatment;

$j=4$: do not work and seek treatment.

[18] An individual's acute illness type is not observed by the econometrician. Although the specific acute illness diagnosis is available in the NMES data (if the illness is recorded), the unobserved illness types defined in the model capture more than the broad classification of acute illness (e.g., infectious and parasitic diseases or respiratory conditions) or the specific 4-digit ICD-9 code (e.g., influenza or acute bronchitis). The illness types also distinguish illnesses by unobserved characteristics such as how treatment intensive, absence intensive, and severe the illnesses are.

An indicator function, d_t^j, indicates the alternative chosen by an individual in period t of an illness where $d_t^j = 1$ if alternative j is chosen during period t of an illness and $d_t^j = 0$ if alternative j is not chosen during the period.[19] Alternatives are mutually exclusive such that $\sum_{j=1}^4 d_t^j = 1$, $\forall t = 1, \ldots, T$.

3.2. *State Variables and Laws of Motion*

The decisions made during period t of an illness depend on the illness, treatment, and absence history of an individual up to period t. This history and the individual's decisions in each period determine the "state" in which he enters a new period. The observed state at the beginning of period t of an illness is described by a vector, denoted $\mathbf{z}_t$, of four variables: the illness type, k; the elapsed length of the current illness, t; the accumulated number of physician visits, v_t; and the accumulated number of illness-related absences from work, a_t. Since duration of an illness is captured by the time period subscript, t, on all variables, it is dropped as a separate component of the state vector.

The state variables evolve in the following way.[20] Because it is assumed that illnesses are mutually exclusive and that an illness cannot develop into a different illness, the illness type (k) does not change over the episode. The number of periods the individual has sought medical treatment during the episode of illness follows the process

$$v_1 = 0,$$

$$v_{t+1} = v_t + (d_t^2 + d_t^4), \quad \text{where}$$

$$(d_t^2 + d_t^4) = \begin{cases} 0 & \text{if no treatment at } t \\ 1 & \text{if treatment at } t \end{cases} \qquad (t = 1, \ldots, T).$$

Similarly, the number of absences from work during an illness episode evolves as

$$a_1 = 0,$$

$$a_{t+1} = a_t + (d_t^3 + d_t^4), \quad \text{where}$$

$$(d_t^3 + d_t^4) = \begin{cases} 0 & \text{if not absent at } t \\ 1 & \text{if absent at } t \end{cases} \qquad (t = 1, \ldots, T).$$

19 The subscript t denotes a specific period of the illness episode. That is, t-subscripted variables represent the level of that variable in the tth period of an illness, not in calendar time. A subscript of $t = 0$ implies a health state free of illness (i.e., the individual is well). The subscript $t = T$ denotes the episode, and hence, decision-making, horizon. Individual subscripts i are ignored throughout this section.

20 The space of all possible states at the beginning of period t is Z_t, where $\mathbf{z}_t = (k, v_t, a_t) \in Z_t$. In period one of an illness episode of type k, there is only one possible state: $\mathbf{z}_1 = (k, 0, 0)$. In general, there are t^2 states at the beginning of period t of an episode of illness.

Once an individual recovers from an illness, the state variables return to zero, the initial conditions for another potential illness episode.[21]

3.3. *Illness and Recovery Probabilities*

The probability of contracting an illness of type k conditional on being well, $\pi^S(k)$, depends on a vector, $\mathbf{H}$, of exogenous health-related and demographic variables such as health status and age.[22] The model assumes that an individual can contract only one illness at a time. Additionally, the probability of moving from one illness type to another within an illness episode is zero, as is the probability that an acute illness will develop into a chronic illness during the episode. The probability of contracting illness type k is

$$(1) \qquad \pi^S(k) = \frac{\exp(\delta_{0k} + \delta_{1k}\mathbf{H})}{\sum_{k'=0}^{K}\exp(\delta_{0k'} + \delta_{1k'}\mathbf{H})}.$$

The specific functional form of the recovery probability, $\pi^W(\mathbf{z}_{t+1})$, must capture the dynamic aspects of biological transition from a state of illness to a well state. Thus, the technological process incorporates the effects of illness duration, medical treatment, work absence, and illness type. The probability of recovery conditional on being ill with illness type k is

$$(2) \qquad \pi^W(\mathbf{z}_{t+1}) = \begin{cases} \dfrac{\exp(\eta_k'\mathbf{E}_{t+1})}{1 + \exp(\eta_k'\mathbf{E}_{t+1})} & \text{if } t = 1, \ldots, T-1, \\ 1 & \text{if } t = T, \end{cases}$$

where

$$\eta_k'\mathbf{E}_{t+1} = \eta_{0k} + \eta_{1k}v_{t+1} + \eta_{2k}(v_{t+1})^2 + \eta_{3k}a_{t+1} + \eta_{4k}(a_{t+1})^2 + \eta_{5k}(v_{t+1})(a_{t+1}) + \eta_{6k}t + \eta_{7k}t^2 + \eta_{8k}t^3 + \eta_{9k}\mathbf{H}.$$

The polynomial terms in the recovery probability capture the potentially non-monotone aspects of medical care effectiveness, recuperation effectiveness, and

[21] While modeling these state variables is important for capturing the dynamic effects of treatment and absence decisions over time, they do not capture all of the important dynamics of the decision-making problem. In addition to the accumulated number of treatment visits and illness-related absences, the timing of treatment and absence may also drive the dynamics of the problem. That is, the probability of recovery on day 7 of an illness is likely to differ depending on whether the individual sought treatment on day 1 or on day 5. Including the entire history of visits and absences would increase the number of states per time period to J^{t-1} where J is the number of alternatives at time t. In this problem, that would amount to over a trillion possible states at T—an unmanageable number of states for solution of the model. Even simply keeping track of the timing of the first visit and absence, as opposed to the timing of all visits and absences, requires an unmanageable state space.

[22] In order to simplify notation I do not list exogenous variables that define the observed heterogeneity of individuals as arguments of functions. These variables, however, are elements of the information that is available to an individual during a decision-making period.

time dependence. The efficacy of treatment may depend on whether an individual continues to work or recuperates at home; the interaction term captures this dependence. The vector **H** denotes the exogenous demographic and health-related variables defined above.[23]

The model assumes that individuals know the type of acute illness they have contracted; that is, they know the illness type, the biological probability of recovery associated with that type, and the longest possible length of the illness duration. This assumption abstracts from learning (i.e., the updating of beliefs about the illness type). Although the length of the longest possible illness episode is technologically given and assumed to be known by an individual, the actual duration of an individual's illness is endogenous.

3.4. *Utility Functions and Budget Constraints*

The utility of an individual who is well, $U^W(\cdot)$, is deterministic and depends only on the composite consumption good, X_t. The utility of an individual who is ill, $U^S(\cdot)$, depends on consumption, the type of acute illness, and the vector of medical care use and work absence choice indicators, $\mathbf{d}_t = (d_t^1, d_t^2, d_t^3, d_t^4)$, at each period t of the illness. Alternative-specific random taste components of utility, $\epsilon_{tk} = (\epsilon_{tk}^1, \epsilon_{tk}^2, \epsilon_{tk}^3, \epsilon_{tk}^4)$, additively affect an individual's utility when ill. The taste parameters represent information known by the individual but unobserved by the econometrician. In addition to being alternative specific, the taste parameters are also individual, time, and illness specific. The per-period linear-additive utility functions[24] are

$$U^W(X_t) = X_t \quad \text{if well,} \tag{3}$$

$$U^S(X_t, k, \mathbf{d}_t, \epsilon_{tk}) = \alpha_{0k} + \alpha_{1k}(d_t^2 + d_t^4) + \alpha_{2k}(d_t^1 + d_t^2) + \alpha_{3k} X_t + \sum_{j=1}^{4} \epsilon_{tk}^j d_t^j \quad \text{if ill.} \tag{4}$$

In order to simplify notation, I denote the utility of an individual who is ill and choosing alternative j as $U_j^S(X_t, k, \epsilon_{tk})$ subsequently.

[23] Acute illness episodes in the past do not explicitly affect the illness and recovery probabilities, nor do they affect the value of being well. I assume that incidence and recovery are independent across illness episodes. The assumption of independence is supported by the work of Keeler and Rolph (1988).

[24] Linear utility implies that the individual is indifferent about the consumption profile over the episode of illness if the rate of interest is equal to the rate of time preference. The model also assumes that the individual cannot carry over any debt incurred during the most recent illness episode to the next episode of illness. That is, the individual must enter the next illness episode with the same characteristics that he entered the previous episode. Experimentation with concave utility functions and debt accumulation required restrictive pay back schemes in order to maintain stationarity of the well value function. Thus, I do not model savings and borrowing; there is no consumption smoothing across health states, nor during the illness episode.

The parameter α_{0k} denotes the utility (or disutility) associated with an illness of a particular type. The parameter α_{1k} allows for a direct utility gain or loss associated with visiting a doctor given the illness type. Thus, α_{1k} enters the per-period utility of an ill individual only when alternative 2 or 4 is chosen during that period. Similarly, α_{2k} captures the utility gain or loss of attending work when ill. These parameters enter utility when an ill individual chooses not to be absent. Lastly, α_{3k} represents the marginal utility of consumption when ill with a particular acute illness.

The per-period budget constraint determines the composite consumption good, X_t. The variable Y denotes per-period labor income. The product pC defines an individual's out-of-pocket cost of a medical visit, which reflects the total price p of a visit[25] and the out-of-pocket rate C, $C \in [0,1]$. The variable C reflects the exogenous proportion of the total price for which an insured individual is responsible. Thus, $C = 1.0$ implies full out-of-pocket payment by the consumer and $C = 0.0$ implies no out-of-pocket payment by the consumer. If an individual is uninsured, then he always faces the full price of medical treatment.

The variable L indicates sick leave coverage. That is, $L = 1$ if an individual has sick leave coverage and $L = 0$ if paid sick leave is not provided. A replacement rate, $\Phi(\cdot)$, represents the proportion of the daily wage that sick leave replaces, and is a logistic function of the accumulated number of absences within the episode. More specifically,

$$\Phi(a_{t+1}) = \frac{\exp(\phi_1 + \phi_2 a_{t+1})}{1 + \exp(\phi_1 + \phi_2 a_{t+1})}.$$

Because the data provide no information on the stock of sick leave days, and because a decision to be absent depends to some extent on the number of paid absence days remaining, the replacement rate is an ad hoc way of accounting for the costs of depleting the stock of paid sick days. Thus, what an individual's sick leave covers is net of this hypothetical cost. The budget constraint is

$$(5) \qquad X_t = \begin{cases} Y & \text{if well,} \\ Y - pC(d_t^2 + d_t^4) - Y(1 - [\Phi(a_{t+1})]L)(d_t^3 + d_t^4) & \text{if ill.} \end{cases}$$

3.5. THE OPTIMIZATION PROBLEM

Conditional on health insurance and sick leave coverage, the objective of an individual who is ill with illness type k is to choose control variables $\mathbf{d}_t = (d_t^1, d_t^2, d_t^3, d_t^4)$ for $t = 1, \ldots, T$ to maximize discounted lifetime expected utility. The function $V_j^S(\cdot)$ denotes expected lifetime utility of an individual who is ill

[25] The price of a medical visit is the same regardless of the illness type. The total price does not vary across the illness episode but may vary across individuals. Allowing the price to change across time would require the modeling of expectations of its value over time. Although it is feasible to model such expectations in dynamic programming problems (e.g., expectations of future wage offers in job search models), the assumption is not adopted in this paper.

and chooses alternative j in period t of the illness. In addition to the state variables k, v_t, and a_t, the information available to an individual at the beginning of period t includes exogenous economic and demographic information, previous choices made up to period t, $\{d_{t'}^1, d_{t'}^2, d_{t'}^3, d_{t'}^4\}_{t'=1}^{t-1}$ and all past and current realizations of the random taste components, $\{\epsilon_{t'k}^1, \epsilon_{t'k}^2, \epsilon_{t'k}^3, \epsilon_{t'k}^4\}_{t'=1}^{t}$. The expression V^W denotes the expected lifetime utility of an individual in any period free of illness.

The maximal expected value of utility when ill, $V^S(\cdot)$, is defined to be the maximum of the expected lifetime utilities of choosing each alternative during a period of illness; that is,

$$V^S(\mathbf{z}_{t+1}) + \mathrm{E}_t\left[\max_{j \in J}\left[V_j^S(\mathbf{z}_{t+1}, \epsilon_{t+1})\right]\right], \quad \forall t.$$

When ill and $t < T$,

$$\begin{aligned} V_j^S(\mathbf{z}_t, \epsilon_t) = {} & \overline{U}_j^S(X_t, k) + \epsilon_{tk}^j \\ & + \beta\left[\pi^W(\mathbf{z}_{t+1})V^W + (1 - \pi^W(\mathbf{z}_{t+1}))V^S(\mathbf{z}_{t+1}) \,|\, d_t^j = 1\right] \end{aligned}$$

and when ill and $t = T$,

$$V_j^S(\mathbf{z}_T, \epsilon_T) = \overline{U}_j^S(X_T, k) + \epsilon_{Tk}^j + \beta V^W.$$

Expected lifetime utility when well is

$$V^W = U^W(X_0) + \beta\left[\left(1 - \sum_{k=1}^{K} \pi^S(k)\right)V^W + \sum_{k=1}^{K} \pi^S(k)V^S(\mathbf{z}_1)\right]. \tag{6}$$

The value of being well, V^W, is the unique fixed point of the stationary process defined in equation (6). Boswell (1994) proves that a stationary value of being well exists.

4. IMPLEMENTING THE THEORETICAL MODEL

The theoretical model presented above explains the medical care consumption and absenteeism decisions of individuals over an illness episode. Solution of the general model produces demand functions that could be approximated by statistical equations and estimated. While such statistical models are useful for showing associations between variables, they are less useful for predicting how behavior may change in response to exogenous changes in policy. Estimation of the structural parameters of the explicit optimization problem provides for a better understanding of factors affecting behavior and for the evaluation of alternative public policies.

Despite the eventual payoff, estimation of the structural parameters is computationally difficult. This difficulty often limits the "size" of the optimization problem that can be solved and estimated. In this section I describe the assumptions that were made in order to estimate the model: I discuss why behavior is limited to acute illness episodes, why health insurance and sick leave coverage are treated as exogenous, and why deductibles and stocks of sick leave are not included. Other minor compromises (but with major computational gains) are discussed in footnotes 16, 21, 24, and 25. Despite some omissions, the estimated model provides a solid foundation for further analysis of health care behavior within a structural, dynamic framework.

In order to fully understand the dynamics associated with medical care consumption in general, an extremely complicated model and an abundance of detailed data are needed. That is, even if the focus is on the partial equilibrium behavior of consumers only, a good theoretical model would include the following: the decision among many health insurance alternatives (e.g., employer-provided, spouse's employer-provided, privately purchased, federally funded) and many characteristics of health insurance (e.g., deductibles, coinsurance rates, maximum deductible amounts, coverage of specific services, family vs. individual coverage, provider type), probabilities of illness and injury for each family member (e.g., varying severities of acute and chronic conditions), and decisions among alternative forms of care (e.g., preventive, diagnostic, curative, physician, hospital, dental, and vision care, prescription drugs, equipment and supplies). The data requirements for estimation of such a model include: characteristics of all plans available to and chosen by an individual or family, dates and characteristics of all illness and injury episodes, dated observations on utilization and charges for every medical service, and changes in demographic and health-related variables over time (e.g., income, insurance coverage, marital status, family size, health status). Thus, data demands, as well as computational demands, make solution and estimation of such a model an ambitious feat.

Given the complexity of modeling contraction of and recovery from the *numerous* illnesses and injuries that may result in medical care consumption and absenteeism, the scope of the model is intentionally restricted to a *specific* class of illnesses. It is assumed that being ill with any of the acute illnesses examined does not alter overall health status after recovery from the illness. This focus allows me to nest the daily decisions during an illness episode within an infinite horizon model and, thus, to avoid solving the individual's daily decision-making problem over his remaining lifetime.

Because modeling the health insurance choice requires modeling the subsequent decisions to consume care and miss work during *all* episodes of illness during the coverage period, the health insurance decisions are not incorporated in the paper.[26] Although health insurance and, likewise, sick leave coverage are assumed to be exogenous, I control for characteristics that influence these decisions such as income, health status, and age. The endogeneity bias, however, is likely to overstate the effects of health insurance and sick leave coverage on medical care use and illness-related absenteeism.

[26] An individual's expected future medical care utilization and expenditures influence the decision to purchase health insurance and the choice among different insurance plans today.

Although health insurance and sick leave coverage constitute observed heterogeneity and, hence, affect the decision-making problem, all of the specific characteristics of such plans do not. For example, I do not incorporate deductibles, a common feature of health insurance, in the theoretical model of individual behavior. Several difficulties contribute to this decision. (i) For reasons mentioned above, the model is limited to decisions about one type of medical treatment and a specific set of illnesses. In general, deductibles, or dollars remaining in one's deductible, are less discerning: payments for *all* covered treatments of *all* covered illnesses reduce the remaining deductible. Accurate modeling of the effects of deductible remainders would require inclusion of every possible illness and every possible treatment alternative. Modeling all of these health transitions and utilization decisions is beyond the scope of this paper. (ii) Despite the computational difficulty, it is impossible to determine the deductible remainder in the NMES data. Insurance plans vary significantly in terms of what procedures are covered and to what degree. Additionally, the beginning date of the accounting period in insurance contracts differs by plan. For example, some plans cover expenses from January to January; others start the insurance year in June. Because the NMES data span the 1987 calendar year, utilization of all services that may have reduced the remaining deductible are available only for individuals whose insurance year began in January. (iii) Even if dollars remaining in one's deductible were available at the beginning of the illness, solution of the model described in Section 3 would require calculation of the well value function for each discretized value of the deductible remainder at each time period. It would expand the model from a stationary problem in which decisions are made over a finite period to a (intractable) lifetime decision-making problem.

Admittedly, determination of the structural parameters of a dynamic stochastic model of optimization behavior requires that theoretical assumptions be made explicit in light of data limitations and solution and estimation complexity. Many assumptions, however, are also embedded in the linear reduced form models prevalent in the health care literature; the assumptions are not easily recognized because a precise model rarely accompanies the empirical work. For example, most empirical studies of health care demand are unable to account for behavior induced by uncertainty due to the implicit assumption of perfect foresight. Similarly, the statistical models do not allow for the dynamic effects of current and past decisions because the specifications typically include only contemporaneous or time-invariant variables. Additionally, the reduced form models do not allow a researcher to disentangle the effects of observed variables. For example, why does health status matter in a model of medical care demand? Estimation of the structural parameters of a behavioral model allows for the explicit effect of health status on preferences for care, as well as probabilities of contracting illness and of recovering from illness. Finally, estimation of the parameters of a well thought out optimization problem permits the introduction and evaluation of alternative public polices that may not be feasible to include in a statistical model. For these reasons I estimate the parameters of the economic model as specified rather than estimating the parameters of an approximation to the decisions or a reduced form statistical model. Comparisons of the estimation results from the behavioral model with those from a similar reduced form model are presented below.

5. ESTIMATION RESULTS

I estimate the parameters of the individual's optimization problem by maximizing the likelihood function defined in equation (B.2) of Appendix B.[27] The following assumptions are made: a period is defined to be a day; the maximum length of an acute illness episode is 21 days;[28] the daily discount factor, β, is constant at 0.9997, which corresponds to an annual discount rate or time preference of ten percent;[29] the cost of a physician visit is \$35.00 and does not vary across the illness episode or across individuals;[30] and the estimated model allows for two unobserved types of acute illness.[31] The utility functions and budget constraints follow the specifications described in equations (3), (4), and (5). The specifications of the illness and recovery probabilities follow that of equations (1) and (2). The baseline health status is excellent with dummy variables indicating whether an individual's health status is good or fair/poor. The baseline age is 25–44 years with a dummy indicating 45–64 years of age. The vector Θ denotes the estimated parameters of the optimization problem.

5.1. *Parameter Estimates*

Table VII displays the estimates and asymptotic standard errors of the utility function parameters, the recovery and illness probability parameters, and the budget constraint parameters. Given the nature of illness, one would expect to

[27] Initially, I use a downhill simplex method to find a set of parameters that are in the area of a local maximum. Once in the vicinity of the maximum, the optimization program switches to a new maximization algorithm that calculates an outer product approximation to the hessian using numerical first derivatives (BHHH) (Berndt et al. (1974)).

[28] Of those individuals observed to have an illness episode, only the first episode is chosen for analysis in order to avoid modeling multiple episodes of illness. Furthermore, I do not include every episode as an independent observation because of possible correlations in behavior across episodes. The likelihood function associated with the full sample is made up of two parts—one consisting of contributions by those individuals observed to have an illness episode; the other consisting of contributions by those individuals not observed to have an illness episode.

[29] Various discount factors were considered in estimation for sensitivity analysis.

[30] Because the total cost of \$35.00 represents the 1987 median physician visit charge for individuals who sought treatment, it is not an accurate measure of the cost of a visit, in general. It is not obvious, however, where the figure lies in the distribution of physician visit costs. Is it at the low end of the distribution, implying that individuals who do not go to a doctor face higher prices, or is it at the high end, implying that those who do seek treatment have more serious illnesses and possibly higher physician visit costs? The estimates were not sensitive to the choice of the mean or median total cost. The use of an average cost measure, however, does not incorporate all of the uncertainty in medical visits costs (i.e., low probability, high cost visits).

[31] Additional unobserved heterogeneity in illness did not improve the fit of the model significantly.

TABLE VII

ESTIMATION RESULTS

Description	Illness of Type 1			Illness of Type 2		
	Θ	$\hat{\Theta}$	ASE	Θ	$\hat{\Theta}$	ASE
Utility Function Parameters						
Utility of illness	α_{01}	−3177.744	11.923	α_{02}	−349.000	391.191
Utility of a physician visit	α_{01}	−89.329	5.289	α_{12}	−67.935	23.508
Utility of not being absent	α_{21}	128.511	5.099	α_{22}	153.783	163.874
Marginal utility of consumption	α_{31}	0.156	0.014	α_{32}	0.582	0.703
Recovery Probability Parameters						
Constant	η_{01}	−2.9694	0.1161	η_{02}	−6.8813	5.3725
Coeff on v_{t+1}	η_{11}	0.0037	0.0004	η_{12}	−0.2467	0.4229
Coeff on v_{t+1}^2	η_{21}	−0.0004	0.0001	η_{22}	0.0757	0.0918
Coeff on a_{t+1}	η_{31}	0.0065	0.0003	η_{32}	−2.6508	1.0725
Coeff on a_{t+1}^2	η_{41}	0.0007	0.0001	η_{42}	1.7572	1.6322
Coeff on $v_{t+1}a_{t+1}$	η_{51}	0.0003	0.0001	η_{52}	0.0677	0.0101
Coeff on t	η_{61}	0.5722	0.0241	η_{62}	0.5309	0.2413
Coeff on t^2	η_{71}	−0.0749	0.0016	η_{72}	−0.0490	0.0390
Coeff on t^3	η_{81}	0.0030	0.0001	η_{82}	0.0013	0.0010
Coeff on good health status	η_{91}	−0.0504	0.0296	η_{92}	−0.3062	0.7538
Coeff on fair/poor health status	$\eta_{10,1}$	−0.1146	0.0434	$\eta_{10,2}$	−0.0260	0.0983
Coeff on 45–64 years of age	$\eta_{11,1}$	−0.0185	0.0263	$\eta_{11,2}$	−0.2843	0.3390
Illness Probability Parameters						
Constant	δ_{01}	−6.6599	0.1092	δ_{02}	−17.6771	4.0939
Coeff on good health status	δ_{11}	0.0340	0.0979	δ_{12}	4.7310	3.8839
Coeff on fair/poor health status	δ_{21}	−0.1742	0.1711	δ_{22}	−0.1348	0.2971
Coeff on 45–64 years of age	δ_{31}	−0.4570	0.0990	δ_{32}	−0.3718	0.1270
Budget Constraint Parameters						
Replacement rate—constant	ϕ_1	5.6491	2.6810			
Replacement rate—coeff on a_{t+1}	ϕ_2	−1.7575	0.8634			
Prop of insured facing 0% OOP						
Constant	θ_{10}	−0.6299	0.2801			
Coeff on good health status	θ_{11}	−0.0311	0.3327			
Coeff on fair/poor health status	θ_{12}	0.1928	0.4848			
Prop of insured facing 20% OOP						
Constant	θ_{20}	−0.5293	0.2815			
Coeff on good health status	θ_{21}	−0.2217	0.3412			
Coeff on fair/poor health status	θ_{22}	1.3314	0.6489			

Note: $\Theta \equiv$ parameter, $\hat{\Theta} \equiv$ parameter estimate, ASE $\equiv$ asymptotic standard error; $\ln \mathscr{L}(\Theta, \theta) = -11608.671$.

find that the constants in the utility functions associated with illness, α_{0k}, are negative. That is, being ill reduces one's utility regardless of the marginal return to consumption and of one's behavior. Because the marginal utility of consumption (or income) is normalized to one in the well utility equation, the units assigned to the utility parameters are dollars. It appears that being ill with an illness of type 1 "costs" (in psychic terms) \$3178.00 per day and being ill with an illness of type 2, \$349.00 per day. In other words, contracting a type 2 illness is comparable to losing three days of income for a middle-income individual. The disutility associated with a type 1 illness is quite a bit larger (equivalent to over a month of earnings). While this estimate strikes one as being an extremely high price to pay to avoid illness, it doesn't seem unreasonable when one considers the discomfort, costs of missing work, and medical care costs associated with an illness of uncertain duration. I provide an interpretation of the illness types once all the type-specific parameters are discussed.

The estimated parameters indicate that the utility derived from an additional unit of consumption when ill, α_{3k}, is less than when well: 15.6% of that when well for an acute illness of type 1 and 58.2% for an acute illness of type 2. Although it has been suggested that the marginal utility of consumption (or income) could be higher when ill than when well because one is willing to pay more for comfort when ill, the data and the current models in the literature used to address the issue cannot verify that claim (Heffley (1982), Hey and Patel (1983), and Viscusi and Evans (1990)). The marginal utilities associated with illness are smaller than those found by Viscusi and Evans (1990) using self-assessed probabilities of injury and wage compensation, but confirm that a departure from a well state reduces the marginal utility of income.

The estimates of α_{1k} reveal that visiting a physician decreases one's daily utility. Although almost the same, a visit to the doctor when one is ill with a type 2 illness is not as "bad" as when the illness is of type 1. While travel time to a physician's office and waiting time at the office are not explicitly modeled, the parameters may be capturing the disutility associated with these activities, in addition to the discomfort associated with treatment.

Individuals also receive utility from attending work while ill (α_{2k}). Initially, this result may seem counterintuitive. In typical labor-leisure models of economic behavior, individuals receive utility from leisure; one could assume that staying home from work provides utility. However, the utility gain from working while ill should be interpreted as a loss associated with absence from work. While sick leave provision and the daily income replacement rate capture the economic costs of absence, the disadvantage of "calling in sick," or the "worry" cost, dominates the utility of not working. Although leisure is not an explicit part of the model, staying home from work when ill should not be interpreted as leisure. An ill individual is not staying home in order to enjoy leisure, but is staying home to recuperate (i.e., to improve his probability of recovery).

The replacement rate, or percent of the wage that is replaced by sick leave coverage, is 98.0% for the first absence of an illness episode. The next absence results in only 89.4% of the daily wage being replaced. Sick leave coverage would replace 59.3% of the daily wage for a third absence. The absence-dependent rate captures the fact that the stock of absence days is not limitless. It also accounts for other costs associated with missing work, even though the employer offers sick leave coverage. Such costs may include depletion of the stock of sick leave days, increased work load upon returning to work, and employer dissatisfaction with employee absences.

Unconditional on health status, almost half of the insured individuals are responsible for 100% of the total cost of a doctor visit, with the other half split evenly between the 0% and 20% coinsurance rates. The model assigns a greater probability of paying the full cost of treatment to those individuals who never seek treatment. That is, these individuals are less likely to have passed their deductible. Although 92% of individuals who are observed to have an illness episode are insured, it may be that, at any point in time, 50% of all individuals are facing a deductible in which case the out-of-pocket responsibility is 100% of the total doctor bill. This observation emphasizes the importance of extending the model to incorporate the economic effects of deductibles (and the complex structure of health insurance, in general) on medical care use behavior. The distribution of insured individuals across coinsurance rates is similar for those in excellent and good health. Interestingly, only 25% of insured individuals in fair or poor health pay 100% out of pocket. As indicated below, those individuals are more likely to seek treatment. Also, only 17% of such individuals face 0% out-of-pocket responsibility. This result suggests the presence of insurance selection issues: higher rates for insurance may discourage purchase of better coverage plans.

The estimated coefficients of the recovery probabilities differ depending on which type of illness an individual has contracted. With illnesses of type 1, visits to a doctor improve the probability of recovery at a decreasing rate. However, with illnesses of type 2, the recovery probability decreases, at a decreasing rate, with the accumulated number of doctor visits. Staying home from work appears to be slightly more effective than treatment among the illnesses examined. Work absences improve the probability of recovery from illness type 1. Although the initial days of recuperation at home have a negative effect on the recovery probability of illness type 2, the benefit of staying home increases dramatically relative to the treatment benefit after two absence days.

Although treatment does improve one's probability of recovery, the benefit is small relative to the effect of time. Within the class of illnesses that I examine (i.e., infectious and parasitic diseases and respiratory conditions), one can think of many illnesses that may not be benefited by treatment. For example, it is known that antibiotics will not fight viral infections, but they may be remedial for bacterial infections. In the former case, recovery simply takes time. The estimates of the effect of health status on the recovery probability reveal that individuals with an overall health status of good or fair/poor have a lower probability of recovery than those in excellent health, ceteris paribus. Similarly, older individuals have a lower initial probability of recovery than younger individuals. The estimation results indicate that, for a given level of accumulated visits and absences, the probability of recovery is increasing with the duration of the illness. Figure 3 depicts the unconditional hazard, or probability of recovery during period t, conditional on not having recovered up to period t but unconditional on the state variables v_t and a_t. Given that the probability of recovery at the end of 21 days is 100%, one would expect to find that the hazard is increasing toward one near the end of the episode of illness.

The parameters of the illness probability equations indicate that illnesses of type 1 are more likely for individuals of each health status and of each age than illnesses of type 2. The daily probabilities defined by the parameter estimates

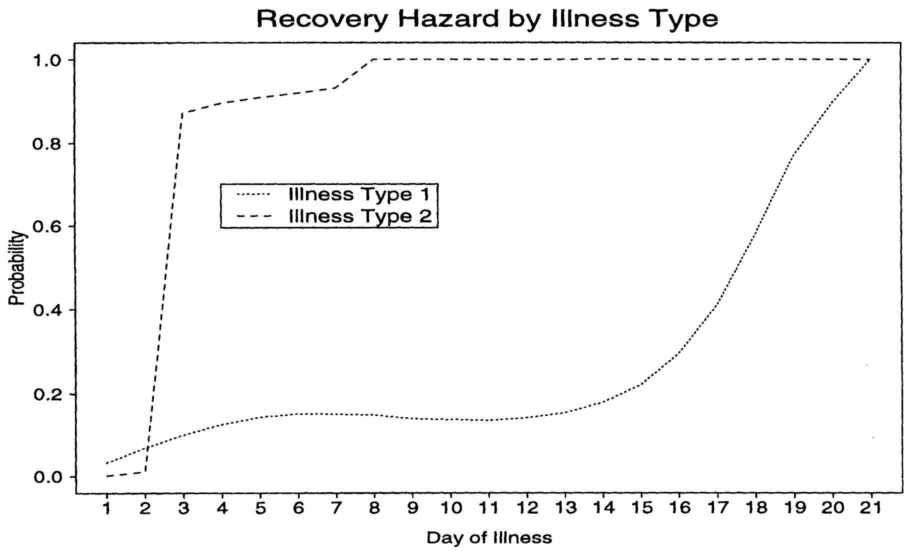


FIGURE 3.—Recovery hazard: unconditional on treatment and absence history.

and the behavioral probabilities associated with illness translate into an 80% chance of not being observed to have an illness episode of those considered over the entire year. That is, the probability of never becoming ill and of not seeking treatment or being absent from work during any illness episode is 80%.

5.2. *Interpretation of Unobserved Illness Types*

As mentioned in Section 3, unobserved illness types are introduced in order to distinguish between illnesses that vary in several unobserved dimensions. That is, illnesses may differ by effectiveness of treatment and absence, by severity, by duration, and by discomfort, among other things. Even a specific observed diagnosis (e.g., acute nasopharyngitis or the common cold) may differ along these dimensions.

In order to provide some interpretation of the estimated parameters associated with contraction of, recovery from, and utility of each type of illness, Table VIII describes the observed characteristics of the most prevalent illnesses in the sample. Each illness is defined by an ICD-9 code (which is one dimension among many of the unobserved illness types in the estimated model). Colds and flu represent the majority (66%) of all observed acute parasitic and infectious diseases and respiratory conditions. These two illnesses, however, differ significantly in their associated characteristics. Illnesses that are often considered less severe, such as colds, upper respiratory infections (URI), and strep throat, have a longer duration than illnesses with more severe symptoms, such as flu and viral infections. However, illnesses with more severe symptoms are less likely to result

TABLE VIII

CHARACTERISTICS OF SPECIFIC ILLNESSES

ICD-9 Illness	%	Length	$p(v>0)$	$E(v)$	$E(v\|v>0)$	$p(a>0)$	$E(a)$	$E(a\|a>0)$
Viral Enteritis	4.13	5.17	0.37	0.37	1.00	0.77	1.37	1.78
Strep Throat	6.20	10.69	0.93	1.00	1.07	0.53	1.60	3.00
Viral Infection	5.37	6.64	0.49	0.59	1.21	0.82	1.44	1.75
Cold	27.41	8.08	0.32	0.33	1.03	0.75	1.18	1.58
URI	3.86	10.11	0.86	1.00	1.17	0.43	0.89	2.08
Flu	38.57	5.38	0.26	0.28	1.07	0.88	1.58	1.80
Other	14.46	9.98	0.82	1.03	1.26	0.49	1.47	2.96

Note: Viral enteritis, strep throat, and viral infection are classified as infectious and parasitic diseases. Cold, upper respiratory infection (URI), and flu are classified as respiratory conditions. The remaining category contains ICD-9 coded illnesses of each classification.

in medical visits. Of the longer duration illnesses, strep throat and URI are treated with near certainty. Absences are more likely among the longer duration illnesses, but episodes of flu, with a relatively short duration and few visits, have the highest incidence of absence. Conditional on any absences, however, episodes of strep throat have the highest average number of absences (and the longest duration).

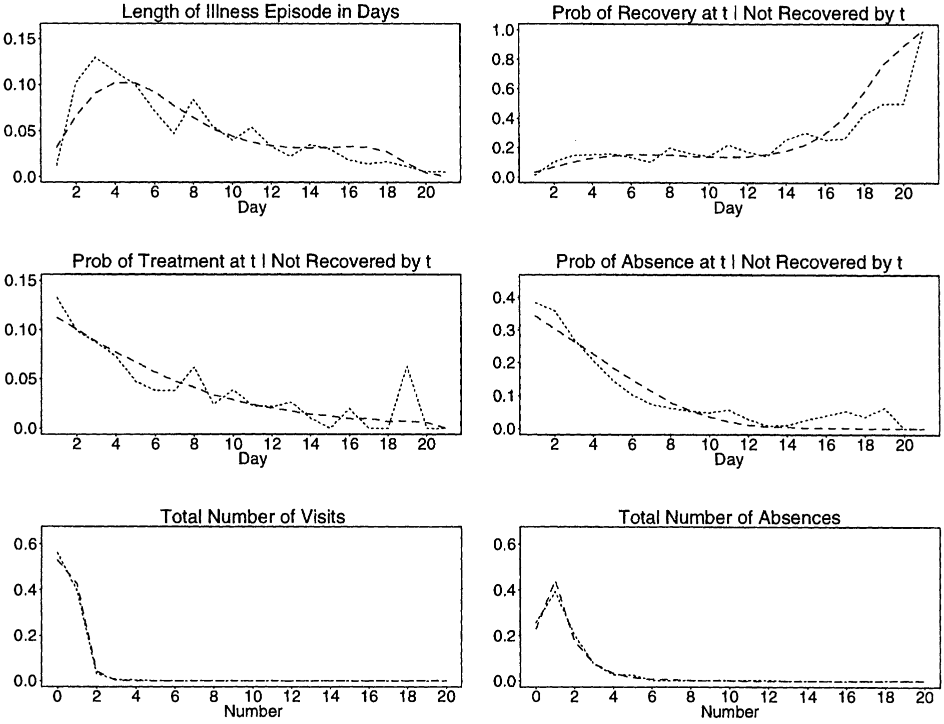
Consequently, it is difficult to give a name to each of the estimated types of illness based on the associated parameter values. Additionally, the unobserved heterogeneity is most likely identifying outliers (as is indicated by the estimated proportions of each illness type) and thus, the illness type representing most of the data contains several different ICD-9 coded illnesses. Efforts to incorporate additional unobserved heterogeneity (i.e., more than two types) did not improve the fit of the model.

In another attempt to provide interpretation of the estimated illness types, I regress the log odds ratio of the two predicted illness types (for each ill individual) on observable illness-related characteristics. The explanatory variables include polynomials and interactions of number of visits and absences, duration of illness, and dummies for the observed ICD-9 coded illnesses listed in Table VIII. (The omitted category is colds.) The only significant variable in some, but not all, regression specifications is the number of visits, indicating that visits are more likely to be associated with illnesses of type 2. This variable is not significant, however, when dummies indicating the ICD-9 code of an illness are included.

5.3. *The Fit of the Model*

In order to assess the ability of the model to capture behavior during an episode of illness, I compare the observed frequencies and predicted probabilities of seeking medical treatment and of missing work, as well as the predicted and observed recovery hazard rates. Because of the censoring problem described in Appendix B (i.e., an illness is observed if and only if treatment is sought or an absence occurs), the analytical calculation of daily predicted behavioral probabilities is quite difficult. Thus, I compute simulated probabilities using 10,000 simulations of each type of individual. Following the qualitative examination, I present more formal goodness-of-fit tests of the model's performance.

It appears that the model does extremely well in capturing behavior over the illness episode as shown in Figure 4. (Note that the spikes in observed probabilities after day 14 are the result of the small number of individuals who remain ill after two weeks.) The model's predictions of illness episode lengths, the recovery hazard, conditional treatment and absence behavior, and total doctor visits and work absences are similar to the observed behavior of the ill sample. Although the timing of visits and absences is not modeled explicitly in the optimization problem, the model captures the timing of first visits and absences rather well as depicted in Figure 5. The predicted probability of the second visit conditional on having at least two visits is also similar to the observed behavior. It is common for patients to return for a follow-up visit one week after the initial visit. Because the timing is not modeled (i.e., the particular day of a visit or the interval between visits is not a state variable), the peak in the probability of a second visit at 7 or 8 days is not captured. This behavior, however, may be explained better by a model that includes physician inducement.



Legend: ....Observed,----Predicted. Probabilities are listed on the *y* axes.

FIGURE 4.—Comparisons of observed and predicted behavior.

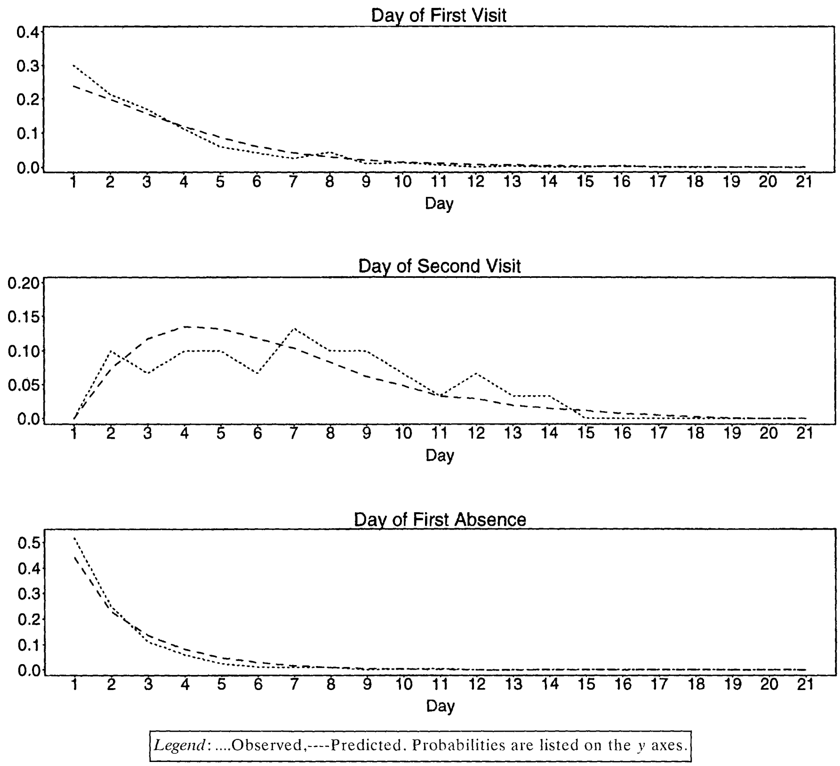


FIGURE 5.—Comparisons of observed and predicted behavior.

The contribution to the likelihood function of individuals who are never observed to be ill (the probability of never being sick or of being ill a certain number of episodes but never seeking treatment or being absent during any of those episodes) is listed in Table IX. The predicted probabilities closely resemble the observed probabilities.

In similar applications of the dynamic programming framework, researchers often use Pearson Chi-square tests to determine whether the probability distribution defined by the economic model generates the observed behavior of the sample. Because the predicted probabilities are functions of the estimated parameters, Pearson's Chi-square test must be modified to correct for the presence of the covariates. That is, appropriate scaling of the Pearson Chi-square statistic is necessary in order to obtain an asymptotically distributed Chi-square statistic, as described by Andrews (1988). Also, the statistic relies on asymptotic theory and is inaccurate in small samples. For this reason, I present goodness-of-fit tests for broad classifications of the sample. Similarly, because the number of individuals remaining ill diminishes as t approaches T, comparisons of the predicted and observed probabilities of seeking treatment (or of being absent) on each day t conditional on not recovering by day t are not feasible. Thus, I perform statistical comparisons of the unconditional probabilities. Table X lists

TABLE IX

OBSERVED AND PREDICTED PROBABILITIES OF NEVER BEING OBSERVED TO BE ILL

Characteristic	Observed	Predicted
Full Sample	0.808	0.809
Daily Income		
Lower	0.840	0.811
Middle	0.796	0.803
Upper	0.785	0.798
Sick Leave		
Available	0.793	0.787
Not Available	0.843	0.839
Health Insurance		
Uninsured	0.884	0.814
Insured	0.799	0.793
Health Status		
Excellent	0.816	0.815
Good	0.780	0.794
Fair/Poor	0.832	0.827
Age		
25–44 Years	0.787	0.786
45–64 Years	0.858	0.850

TABLE X

RESULTS FROM GOODNESS-OF-FIT TESTS

		Treatment		Absence		Episode Length	
Characteristic	Obs.	χ^2 stat.	p-value	χ^2 stat.	p-value	χ^2 stat.	p-value
Ill Sample	726	14.82	0.79	11.82	0.92	26.22	0.16
Daily Income							
Lower	216	17.06	0.65	16.62	0.68	39.55	0.01
Middle	308	13.76	0.84	12.86	0.88	19.24	0.51
Upper	202	22.27	0.33	5.97	0.99	13.43	0.86
Sick Leave							
Available	534	13.43	0.86	14.45	0.81	21.21	0.39
Not Available	192	16.18	0.71	7.91	0.99	114.52	0.00
Health Insurance							
Uninsured	51	903.07	0.00	122.57	0.00	53.07	0.01
Insured	675	16.46	0.69	13.08	0.87	25.07	0.20
Health Status							
Excellent	231	17.51	0.62	3.75	0.99	28.61	0.10
Good	421	8.30	0.99	16.37	0.69	20.11	0.46
Fair/Poor	74	23.15	0.28	17.69	0.61	12.70	0.89
Age							
25–44 Years	559	32.67	0.04	14.72	0.79	18.99	0.53
45–64 Years	167	8.20	0.99	15.47	0.75	30.05	0.07

Note: χ^2 stat. is the chi-square statistic; p-value is the probability value; obs. is the number of observations; degrees of freedom = 20.

the results of tests comparing the predicted probabilities of seeking treatment and of being absent over the illness episode with the observed behavior of individuals in the ill sample. In most cases the hypothesis that the observed proportions and the predicted probabilities come from the same population probability distribution is not rejected at conventional significance levels.[32]

6. POLICY EXPERIMENTS

I conduct several policy experiments to assess the effects of changes in the constraints faced by individuals who become ill. Baseline predictions for optimal behavior described by the model are listed in Table XI. The baseline average number of physician visits is 0.52 per episode and the average number of acute illness-related absences is 1.45 per acute illness episode. The numbers represent a weighted average over a simulated sample of 10,000 individuals of each daily income, sick leave coverage, health insurance coverage, health status, and age. Conditional on at least one doctor visit, the average number of doctor visits per episode is 1.10. The average number of illness-related work absences conditional on at least one absence is 1.88 per episode. Over 53% of the simulated sample do not seek treatment during the acute illness episode; 23% are not absent from work during the illness. The average length of an illness episode is 7.93 days, which is slightly larger than that of the observed sample.

6.1. *Comparisons to Reduced Form Results*

It is useful to compare the predictions based on estimation of the behavioral model parameters with those from a reduced form model similar to that found in the health care literature. It is not straightforward, however, to write down a reduced form model of outcomes that are comparable to the outcomes of the optimization problem described in this paper. That is, the behavioral model allows for the censoring correction that cannot be implemented in a simple reduced form model, allows for illness transitions that cannot be estimated in a reduced form analysis using censored illness data, and allows for policy alternatives that cannot be tested in the reduced form model. Despite this, I estimate two separate reduced form models that describe the following observations. Model 1 includes three separate two-part models for the probability of any episodes and the length of an episode conditional on any, the probability of any

[32] The Andrew's corrected Pearson Chi-square tests indicate that the model does a relatively poor job of fitting the behavior of uninsured individuals. It is likely that individuals with no formal health insurance actually face a zero cost for some medical visits (as opposed to 100% of the total cost) either through free physician care or emergency room care. In other words, the budget constraint may be modeled inaccurately for some uninsured individuals. Thus, the model's prediction of behavior under alternative policies may overstate changes among the uninsured. Similarly, because the effects of passing one's deductible are not incorporated (i.e., the effect of the deductible remainder is not allowed to influence current behavior or future expectations) and the insurance decision is not modeled, the parameter estimates are likely to be biased. Recall, however, that attempts to control for adverse selection (without modeling the insurance decision) are included by allowing the probability of a particular out-of-pocket responsibility to be a function of one's health status.

TABLE XI

PREDICTED TREATMENT AND ABSENCE BEHAVIOR—BASELINE

Characteristic	$p(v=0)$	$E(v)$	$E(v \mid v>0)$	$p(a=0)$	$E(a)$	$E(a \mid a>0)$	$E(T)$
Observed Data	0.56	0.49	1.13	0.26	1.41	1.90	7.35
Full Sample	0.53	0.52	1.10	0.23	1.45	1.88	7.93
Daily Income							
Lower Income	0.52	0.53	1.11	0.23	1.61	2.09	7.91
Middle Income	0.53	0.52	1.10	0.23	1.40	1.82	7.92
Upper Income	0.53	0.51	1.10	0.22	1.28	1.65	7.97
Sick Leave							
Available	0.56	0.49	1.11	0.18	1.57	1.92	7.84
Not Available	0.45	0.60	1.10	0.35	1.13	1.74	8.16
Health Status							
Excellent	0.53	0.52	1.09	0.25	1.27	1.68	7.81
Good	0.53	0.52	1.11	0.23	1.46	1.89	7.97
Fair/Poor	0.52	0.54	1.13	0.19	1.91	2.35	8.06
Age							
25–44 Years	0.53	0.52	1.10	0.23	1.41	1.85	7.92
45–65 Years	0.53	0.52	1.11	0.21	1.55	1.97	7.95
Health Insurance							
Insured 0% OOP	0.48	0.58	1.12	0.25	1.42	1.89	7.92
Insured 20% OOP	0.50	0.56	1.12	0.24	1.44	1.90	7.93
Insured 100% OOP	0.56	0.47	1.09	0.21	1.46	1.86	7.93
Uninsured 100% OOP	0.57	0.47	1.09	0.21	1.46	1.85	7.95
Illness Type							
Type 1	0.53	0.52	1.10	0.23	1.45	1.88	7.94
Type 2	0.96	0.04	1.02	0.00	2.99	2.99	3.13

Note: All probabilities are conditional on having an episode of illness.

visits and the number of visits conditional on any, and the probability of any absences and the number of absences conditional on any. Model 2 contains a probit equation for the probability of being observed to have at least one episode of acute illness, two separate logit equations for the probability of any medical care visits and any absences conditional on having an illness episode, two separate multinomial logit equations for the probability of a specific number of visits or absences per episode, conditional on having any visits or absences (which implies having an episode), and a linear equation for the length of an illness. The last equation incorporates the predicted number of visits and absences from the earlier equations.[33]

[33] Model 1 does not distinguish between having zero visits because one was not ill and having zero visits although one was ill (and likewise for absences). This model most closely matches models in the health care literature, but does not allow one to study within episode behavior. Notice that Model 2 conditions endogenous behavior within an episode on being *observed* to have an episode of acute illness. This model most closely resembles the behavioral model, but suffers from bias associated with the censoring problem (which is accounted for in estimation of the behavioral model). The inability to observe all individuals who are ill (due to censoring of the reported data) suggests that the first model may be more appropriate, but it still differs considerably from the behavioral model. Thus, it is difficult to compare predictions from the reduced form models with those from the behavioral model. Although several results from the models are presented in the paper, complete results may be obtained from the author.

In Table C.I of the Appendix, I show that the reduced form models do a good job of replicating the averages observed in the data but do not appear to capture the range of predictions to the extent of the behavioral model. The reduced form models accurately predict that 19% of the sample is observed to have an acute episode of a respiratory condition or an infectious and parasitic disease.[34] Among the ill individuals, the average number of physician visits per episode is 0.49 and the average number of absences is 1.41. Additionally, 56% of the sample are predicted to have zero visits during an illness episode and 26% have zero absences. The predicted average duration of 7.35 days fits the observed values more accurately than the predictions of the behavioral model. While the reduced form model is a good predictor of observed behavior, it produces behavior in unexpected directions when alternative policies are introduced. Comparisons of predicted outcomes from the behavioral model and the reduced form model under different public policy scenarios are provided in Tables C.II and C.III of the Appendices.[35]

6.2. *Experiment* 1: *Change in One Policy Instrument*

The U.S. government has considered extending health insurance to all individuals through the workplace, purchasing cooperatives, and government subsidies. Included in some proposals is universal access to health care where a basic level of health care services, including physician services, is covered. Thus, the coinsurance rate or percent paid out of pocket could be zero for all individuals. Without changing any other characteristics of the simulated sample, I allow each individual in policy experiment 1 to be responsible for 0% of the cost of a doctor visit. The behavioral model's predictions of treatment and absence under each alternative policy are described in Table XII. Physician visits per episode increase by almost 12%. The number of individuals with zero visits during the episode decreases by 8.8%. The individuals in poorest health increase their visits by a larger percentage than those in the other health status groups. Individuals with sick leave coverage have a higher percentage increase in average visits but those without sick leave have a larger decline in the proportion with zero visits. At a minimum, this policy change would cost $20.40 per episode for each ill worker. This figure represents the cost to the government of such a policy change as it impacts those individuals who are observed to have an illness episode. Additionally, many of those for whom an episode is not observed (because they did not seek treatment and were not absent) may now visit a physician. The probability of being observed to have an illness episode increases

[34] All of the predictions from the reduced form models are similar whether using the set of independent variables found in the paper (daily income, health insurance status, sick leave availability, health status, and age) or using these variables and additional demographic variables such as race, marital status, and education.

[35] The reader is reminded that predictions from all models relate to behavior associated with a particular class of acute illnesses and behavior associated with one episode of illness. Because all policies tested in the behavioral model could not be implemented in the reduced form models, comparisons are made only where feasible.

TABLE XII

PREDICTED PERCENTAGE CHANGE IN TREATMENT AND ABSENCE BEHAVIOR UNDER POLICY EXPERIMENTS 1–3

Characteristic	Exp. 1				Exp. 2				Exp. 3			
	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$	$p(v=0)$	$E(v)$	$p(a=0)$	$E(a)$
Full Sample	−8.75	11.50	9.47	−1.70	−3.00	5.57	−13.07	10.59	32.17	−38.22	−27.27	−6.08
Daily Income												
Lower Income	−8.64	11.40	8.77	−1.17	−2.47	5.40	−16.88	14.96	33.37	−39.10	−28.11	−11.26
Middle Income	−8.89	11.69	10.12	−2.08	−2.90	5.34	−12.33	9.02	31.84	−37.88	−27.27	−5.43
Upper Income	−8.70	11.39	9.42	−2.07	−3.94	6.13	−8.39	4.37	30.85	−37.41	−26.04	−.47
Sick Leave												
Available	−8.28	12.21	10.24	−1.21	−8.28	12.21	10.24	−1.22	31.72	−42.11	−33.11	−5.05
Not Available	−9.97	9.70	7.67	−2.94	14.30	−8.87	−45.01	51.14	40.11	−34.85	−29.22	−.89
Health Status												
Excellent	−8.01	10.56	8.76	−2.13	−2.67	4.88	−9.05	7.21	32.44	−38.18	−30.02	0.00
Good	−9.07	11.83	9.92	−1.77	−3.09	5.58	−13.70	10.88	32.00	−38.15	−26.88	−6.45
Fair/Poor	−9.24	12.52	9.24	−.51	−3.46	7.29	−23.69	15.04	32.36	−38.85	−18.43	−17.66
Age												
25–44 Years	−8.77	11.50	9.47	−1.84	−2.81	5.26	−13.20	10.94	32.29	−38.20	−28.12	−5.07
45–65 Years	−8.69	11.53	9.46	−1.34	−3.57	6.46	−12.67	9.62	31.82	−38.32	−24.68	−8.61
Health Insurance												
Insured 0% OOP	−.13	0.11	0.43	−.21	6.19	−5.23	−20.05	12.25	37.06	−37.38	−25.70	−6.30
Insured 20% OOP	−3.17	3.77	3.36	−.73	2.43	−1.33	−18.56	11.55	35.37	−38.01	−26.64	−6.40
Insured 100% OOP	−14.83	22.78	18.25	−2.88	−9.31	16.06	−5.76	9.30	28.76	−38.94	−28.58	−5.83
Uninsured 100% OOP	−14.64	22.76	18.00	−3.16	−9.23	16.16	−6.90	9.17	27.95	−38.83	−27.88	−6.41
Illness Type												
Type 1	−8.76	11.51	9.47	−1.71	−3.01	5.56	−13.07	10.59	32.23	−38.22	−27.27	−6.11
Type 2	−2.47	66.03	0.00	0.00	−2.47	66.08	0.00	0.00	3.63	−95.40	0.00	0.00

Notes: Exp. 1: 0% out of pocket, sick leave coverage unchanged; Exp. 2: 0% out of pocket, sick leave covered; Exp. 3: prohibit physician visits during first 3 days of illness. All probabilities are conditional on having an episode of illness. $p(v), p(a)$: probability of zero visits (absences); $E(v), E(a)$: average # of visits (absences) ≥ 0 per episode.

by almost 4%, with the largest increases among individuals who face full responsibility for their treatment costs.[36] The probability of any absences conditional on an episode falls by 9.5% and the average number of absences per episode decreases slightly. Thus, it appears that absences and visits are substitutes. The change in average illness duration is negative, but nearly negligible.

Each of the reduced form models produces similar predictions of the change in probabilities of being observed to be ill and the changes in illness duration. The percentage changes in treatment and absence behavior, however, are much smaller in absolute value than the changes produced by the behavioral model. While the unconditional probability of any visits increases under this policy scenario, the within episode treatment behavior responds in the unexpected direction when medical care visits are fully insured: the reduced form models do predict a modest increase in the average number of visits (1.6%), but also indicate that visits during an illness fall by 2%. While this result can be rationalized by improvements in health due to improved access to care, the reduced form model is static and does not incorporate a health production function. The failure of the reduced form model to account for the censored data produces the unexpected result. Both the probability of absence and the average number of absences increases. If visits and absences are complements, then one might expect an increase in medical care cost coverage to produce more illness-related absences. However, the behavioral model, which accounts for the censoring problem, clearly indicates that extension of health insurance coverage lowers the probability of absence. Thus, an interpretation of visits and absences as substitutes or complements is compromised.

6.3. *Experiment* 2: *Change in Two Policy Instruments*

The policy scenario in Experiment 1 involves a change in only one economic constraint. Combinations of policy alternatives, however, may result in significant differences in behavior. For example, allowing no changes in sick leave policy in Experiment 1 implies that individuals for whom sick leave coverage is not available would still face the costs associated with missing work in order to receive the free medical services. Because sick leave coverage is more prevalent among high wage jobs than among low wage jobs, one would expect to see differences in utilization across income types. Thus, if the purpose of a policy change is to improve access to medical care for the poor, then the indirect costs of work loss should be considered in addition to the direct costs associated with utilization.

[36] The overall insurance elasticity of demand for physician services, which can be thought of as a price elasticity, is -0.13. The insurance elasticity for individuals previously paying 100% of the costs is -0.23. Other experiments with changes in the price of treatment generate a price elasticity of -0.12. Although the elasticities are likely to be overstated, they are no worse (upwardly biased) than the elasticities obtained from the 1974–1982 Health Insurance Experiment (Manning et al. (1987) and Keeler, Manning, and Wells (1988)). Like the Rand results, they fall within the low end of the range reported in the health care literature in general.

A second experiment involves extending 0% out-of-pocket costs and providing paid sick leave coverage to all individuals. Under this policy the average number of absences increases by 10.6%, with a 13.1% decrease in the proportion of individuals with zero absences. At the same time, the number of doctor visits increases by 5.6%. The increase in absenteeism is largest among individuals in fair or poor health, individuals previously without sick leave coverage, and individuals with less out-of-pocket responsibility. Among those with at least one absence, individuals previously facing 100% of the cost of medical care have the largest increases in their average number of absences. This policy appears to have the greatest effect in lowering the average illness duration (1.2%) out of several combinations of health insurance and sick leave changes.[37] Reduced form estimates produce responses in similar directions but in smaller magnitudes.

6.4. *Experiment* 3: *Use of a New Policy Instrument*

One advantage of estimating the structural parameters of the individual's optimization problem is that it allows for the introduction of policies that are not observed in the data. The discussion of national health insurance has produced fears, perhaps unfounded, of long waits for medical treatment. While any evidence of queuing is generally found among surgical procedures, it is worth investigating the effects of queues or time restrictions for physician care. Experiment 3 involves restricting access to medical care during the first three days of an illness episode. (Such a scenario cannot be introduced in the reduced form model.) This scenario results in a 38.2% decrease in the average number of visits per episode. The only relative differences among groups are found with regard to sick leave coverage. Individuals without sick leave coverage are more likely to never visit a physician during the episode than covered individuals. However, the average number of visits falls more dramatically among those with sick leave coverage. The proportion of individuals with no absences falls by 27.3%, implying that people are more likely to stay home and recuperate. Under this policy, however, the average number of absences falls by 6.1%. The decrease can be attributed to the 13.1% decrease in the average number of absences among individuals with at least one absence. Thus, while more individuals are absent, they are absent for a shorter amount of time. Because the average length of illness episodes increases by over 7%, the behavior described above indicates that visits and absences are often complements. That is, despite being ill longer, individuals decrease their consumption of both visits and absences.

[37] Another experiment involving two policy instruments maintains 0% out-of-pocket costs but eliminates all sick leave coverage. The largest increase in overall medical care utilization occurs under this policy, with a 33.9% increase in the average number of visits within an episode. The proportion of individuals with zero absences increases by 89.5%; thus, the average number of absences falls by 35.7%. The substitution between absenteeism and medical care is extremely evident with this policy. The policy also extends the average length of illness episodes by almost 4%.

7. CONCLUSION

In this paper, I have developed and estimated a dynamic stochastic model of a worker's medical care utilization and absenteeism during an episode of acute illness. The behavioral framework allows for predictions of the probabilities of seeking treatment, missing work, and recovering on each day of the illness episode. The approach also allows one to examine the impact of various public policies that alter the constraints faced by the worker.

The research makes several contributions to the health care literature. Existing models of medical care utilization do not adequately capture the dynamic aspects of health care demand with regard to economic behavior and biological health transitions. As is evident by this paper, the behavior of individuals over an illness episode is influenced by dynamic outcomes associated with treatment and absence decisions. The paper also explores an area of behavior that has not been studied previously—the behavior of individuals during an episode of illness. The health care literature consists of numerous conclusions about health care demand that are based on health care consumption data aggregated over a year or over an episode of treatment. Analyzing health care consumption over an illness episode provides a better unit of observation for studying the effects of policy intervention. The greatest limitation of the model involves assumptions to avoid computational difficulty. Despite some restrictive assumptions, the model's performance, both qualitative and statistical, is extremely good. The modeling framework and estimation method can be used to extend the current analyses to multiple episodes of illness that might allow for changes in health status over time as a result of behavior during an illness. Allowing for endogenous health insurance, dynamic effects of health insurance characteristics, and changes in health status over time will generate more accurate and applicable policy predictions.

Policy simulations based on the estimated theoretical model reveal substantial responses during an episode of illness to economic incentives. These impacts operate through both physician visits and work absences. Two examples are: (i) Changes in health insurance from 0% out-of-pocket responsibility to 100% out-of-pocket responsibility results in a 20% decrease in physician visits per episode, and (ii) when physician visits are fully covered, a change from no sick leave coverage to provision of sick leave coverage produces a 45% increase in illness-related absences per episode. Generally, medical treatment and work absenteeism appear to be substitutes during an illness episode. For the class of illnesses that I examine (acute infectious and parasitic diseases and acute respiratory conditions), I find that absences are 50% more common than doctor visits. While a day off of work can be more expensive than a doctor visit, being absent is more effective in improving the probability of recovery than is going to the doctor for these acute illnesses. However, with a policy that restricts access to physician visits during the first three days of an illness, both the average number of visits and absences fall while the duration of the illness lengthens. Such behavior indicates that treatment and absences may be complements. This research reveals that sick leave availability, as well as health insurance, should be an important consideration in the evaluation of alternative health care reform proposals.

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APPENDICES

A. Solution of the Optimization Problem

To solve the dynamic programming problem, an assumption must be made about the distribution of the unobserved random taste components that affect utility. The assumption of an additively separable taste parameter that is independent and identically extreme value distributed is convenient because it implies a closed form solution of the period t expected maximum over each possible alternative in period $t+1$. Thus, the assumption eliminates the need for multi-dimensional integration (Rust (1987)).[38]

Solution of the individual's discrete choice optimization problem involves backward substitution. For each value of the well value function in iteration toward the fixed point, the finite horizon dynamic programming problem must be solved. Once the stationary well value is determined, the dynamic programming problem is solved one more time to produce probabilities of behavior during the episode. Because of the recursive structure of the dynamic programming framework, once the probabilities for the period $t+1$ decisions are calculated, the only information that is necessary for solution of the period t problem is the value of the state variables at the beginning of period t and the period t expected maximum over each possible alternative in period $t+1$. Solution of the model produces the probabilities of contracting each illness type, $\pi^S(k)$; the daily probabilities of recovery from each illness type, $\pi^W(\mathbf{z}_t)$; and the daily probabilities of choosing each of the J alternatives conditional on the period t state variables, $\mathrm{p}(d_t^j = 1 | \mathbf{z}_t)$. Additionally, the probabilities of choosing the jth alternative in each period t have the multinomial logit form

$$\mathrm{p}(d_t^j = 1 | \mathbf{z}_t) = \frac{\exp \dfrac{\bar{V}_j^S(\mathbf{z}_t)}{\rho}}{\sum_{j'=1}^{J} \exp \dfrac{\bar{V}_{j'}^S(\mathbf{z}_t)}{\rho}}, \quad \forall t$$

where $\bar{V}_j^S(\mathbf{z}_{t+1}) = V_j^S(\mathbf{z}_{t+1}, \epsilon_{t+1}) - \epsilon_{t+1}^j$ and ρ is a parameter of the extreme value distribution function.[39] The behavioral probabilities and the transition probabilities associated with illness and recovery form an individual's contribution to the likelihood function.[40]

[38] The assumption of an extreme value distribution implies that the additive unobserved components are uncorrelated along each dimension (time, alternative, illness, and individual). The model, however, does allow for illness correlation across time. It is individual unobserved preferences that are not serially correlated. While correlation might be expected (especially across time within an illness), any evidence of an incorrect assumption is determined by the model's fit.

[39] The extreme value distribution has mean $\xi + \rho\gamma$ and variance $\pi^2\rho^2/6$, where γ denotes Euler's constant.

[40] All probabilities are also conditional on an individual's observed characteristics (i.e., daily income, sick leave status, health insurance status, health status, and age), but the equations presented in the paper do not explicitly reflect that conditioning in order to reduce notation.

B. Construction of the Likelihood Function

The likelihood function represents the probability of the observed behavior of individuals in the full sample and not simply those observed to have an illness episode. Let $\bar{I}$ denote the set of individuals who are observed to have an acute illness episode. Individuals for which an illness episode is not observed belong to the set $\tilde{I}$ where $\tilde{I} \cap \bar{I} = \varnothing$ and $\tilde{I} \cup \bar{I} = I$, the set of all individuals in the full sample. Thus, the likelihood associated with the full sample is made up of two parts: one consisting of contributions by those individuals observed to have an illness episode, $\bar{I}$; the other consisting of contributions by those individuals not observed to have an illness episode, $\tilde{I}$.

Contribution of Individuals Never Observed to be Ill

As mentioned in Section 2, the survey records information about an illness episode (including that it occurred) if and only if the individual sought treatment or missed work at least once during the episode. I begin by defining the likelihood contribution of individuals never observed to be ill. Despite the fact that information on beginning and ending dates of illness episodes that did not involve treatment or absence (and the number of such episodes) is unavailable, the probability of such behavior can be constructed from the probabilities derived from solution to the dynamic programming problem.[41] Consider the set of individuals, $\tilde{I}$, for which an illness episode is not observed over the entire survey period. Let E denote the number of illness episodes during the year. Let N be the total number of treatment visits and illness-related absences during all illness episodes. The analytical form of the probability of not being observed to have an acute illness episode, $\mathrm{p}(i \in \tilde{I})$, consists of the probability that an individual never contracted an acute illness throughout the entire year, $\mathrm{p}(E=0)$, plus the probabilities that e acute illness episodes occurred but none involved a doctor visit or an absence, $\mathrm{p}(E=e \cup N=0)$. The probability of zero episodes in one year is

$$\mathrm{p}(E=0) = \binom{365}{0}\left(\sum_{k=1}^{K} \pi^S(k)\right)^0 \left(1 - \sum_{k=1}^{K} \pi^S(k)\right)^{365-0} = \left(1 - \sum_{k=1}^{K} \pi^S(k)\right)^{365}$$

where $\pi^S(k)$ is the daily probability of contracting an illness of type k defined in the optimization problem of Section 3. Note that the assumption of mutually exclusive illness episodes is maintained. (One cannot contract more than one type of illness in one episode.) The probability of e episodes and choosing alternative one (to not seek treatment and to not miss work) every period of each illness episode is

$$\begin{aligned}\mathrm{p}(E=e \cup N=0) = \sum_{l_e=1}^{T} \cdots \sum_{l_1=1}^{T} \Bigg[\prod_{u=1}^{e} \Bigg(&\binom{365 - (\Sigma_{t'=1}^{u-1} l_{t'})}{1} \\ &\cdot \sum_{k=1}^{K} \left(\pi^S(k) \left[\prod_{t=1}^{l_u} ((1-\pi^W(\mathbf{z}_t))\mathrm{p}(d_t^1 = 1 \mid \mathbf{z}_t))\pi^W(\mathbf{z}_{l_u+1}) \right] \right) \Bigg) \\ &\cdot \left(1 - \sum_{k=1}^{K} \pi^S(k)\right)^{365-(\Sigma_{t'=1}^{u} l_{t'})} \Bigg]\end{aligned}$$

where l_e denotes the length of the eth episode. Thus, the contribution of individuals never observed to be ill is

$$\text{(B.1)} \qquad \mathrm{p}(i \in \tilde{I}) = \mathrm{p}(E=0) + \sum_{e=1}^{\bar{E}} \mathrm{p}(E=e \cup N=0).$$

[41] This correction is feasible because of the explicit modeling and estimation of behavior that generates the censoring.

In this calculation, the beginning and ending dates of illnesses that did not involve treatment or absence are not necessary for identification. Only an individual's observed characteristics (i.e., daily income, sick leave status, health insurance status, health status, and age) are needed.[42]

Contribution of Individuals Observed to be Ill

The contribution to the likelihood function of individuals who are observed to have an acute illness episode, $\bar{I}$, consists of behavior prior to and during the observed illness episode. Behavior prior to the observed illness episode equals equation (B.1), replacing the number 365 with the elapsed number of days, denoted f, prior to the first observed illness episode. Let E^f represent the number of episodes in the f days prior to the first observed illness and N^f, the number of visits or absences during the episodes occurring within those f days. The probability of never having a recorded acute illness in f days, $\mathrm{p}(E^f = e \cup N^f = 0)$, is

$$\mathrm{p}(E^{f_i} = e \cup N^{f_i} = 0) = \sum_{l_e=1}^{T} \cdots \sum_{l_1=1}^{T} \left[\prod_{u=1}^{e} \binom{f_i - (\sum_{v=1}^{u-1} l_v)}{1} \cdot \sum_{k=1}^{K} \left(\pi^S(k) \left[\prod_{t=1}^{l_u} ((1 - \pi^W(\mathbf{z}_t))\mathrm{p}(d_t^1 = 1 | \mathbf{z}_t)) \pi^W(\mathbf{z}_{l_u+1}) \right] \right) \cdot \left(1 - \sum_{k=1}^{K} \pi^S(k) \right)^{f_i - (\sum_{v=1}^{u} l_v)} \right].$$

Once an illness episode is observed, the probability of observing one's particular behavior over that episode completes his contribution to the likelihood function. The symbol denoting any choice sequence and recovery history of an individual with the characteristics of individual i is b_i. The probability of observing behavior b_i conditional on having an illness of type k is

$$\mathrm{p}(b_i | k) = \left(\prod_{t=1}^{T_i} \left[(1 - \pi^W(\mathbf{z}_t)) \prod_{j=1}^{J} \mathrm{p}(d_{it}^j = 1 | \mathbf{z}_t)^{d_{it}^j} \right] \right) \cdot \pi^W(\mathbf{z}_{T_i+1})$$

where T_i denotes the last day of the acute illness episode for individual i. Thus, the data necessary for identification of the parameters includes the date of the first illness episode (f_i), one's behavior during the episode ($b_i = \{\mathbf{d}_{it}\}_{t=1}^{T_i}$), the recovery date ($T_i$), and observed heterogeneity.

The Likelihood Function for the Full Sample

Unobserved Illness Types

The expression ν_k represents the probability that the illness contracted is a type k illness out of K possible acute illness types. This expression is a function of the time-invariant daily probabilities of contracting illnesses of specific types conditional on being well, $\pi^S(k)$, that were defined in Equation 1 of Section 3. More specifically,

$$\nu_k = \frac{\pi^S(k)}{\sum_{k'=1}^{K} \pi^S(k')}.$$

[42] Given that T, the maximum modeled length of an acute illness episode, is 21 and $\bar{E}$, the maximum number of acute illness episodes in one year, is theoretically 365 (each episode could last one day), the probability defined in Equation B.1 would take months of computer time to solve once. It is impossible to use the analytical probability in estimation where it would be solved once per individual type at each iteration of the parameters. Thus, for computational tractability, I set $\bar{E}$ equal to two. Allowing $\bar{E}$ to be three does not change the parameter estimates significantly.

Let Θ denote the vector of estimated parameters of the optimization problem. Incorporating information on all individuals in the full sample, the likelihood is

$$\mathscr{L}(\Theta)=\prod_{i\in\bar{I}}\left[\left(\sum_{e=0}^{\bar{E}}\mathrm{p}(E^{f_i}=e\cup N^{f_i}=0)\right)\sum_{k=1}^{K}\nu_k\pi^S(k)\mathrm{p}(b_i|k)\right]\cdot\prod_{i\in\tilde{I}}\mathrm{p}(i\in\tilde{I}).$$

Unobserved Out-of-Pocket Responsibility

For some individuals, the out-of-pocket percentage is not observed. That is, information on the insured's out-of-pocket responsibility for health care costs is known only if the individual visits a doctor during an episode of illness. I can, however, determine the probabilities of choosing each alternative conditional on each insurance classification and weight these probabilities by the probability of each insurance classification. Let U represent the set of uninsured individuals. Let θ_j denote the proportion of the insured who face out-of-pocket percentage j (either 0%, 20%, or 100%). Assuming that no information on individual out-of-pocket responsibility is available, the likelihood function involving the full sample is

$$\begin{aligned}\mathscr{L}(\Theta,\theta)=\prod_{i\in\bar{I}}&\left\{\left[\sum_{j=1}^{3}\theta_j\left(\left(\sum_{e=0}^{\bar{E}}\mathrm{p}(E^{f_i}=e\cup N^{f_i}=0|j)\right)\sum_{k=1}^{K}\nu_k\pi^S(k)\mathrm{p}(b_i|j,k)\right)\right]^{1(i\notin U)}\right.\\&\left.\cdot\left[\left(\sum_{e=0}^{\bar{E}}(\mathrm{p}(E^{f_i}e\cup N^{f_i}=0|i\in U))\sum_{k=1}^{K}\nu_k\pi^S(k)\mathrm{p}(b_i|i\in U,k)\right)\right]^{1(i\in U)}\right\}\\&\cdot\prod_{i\in\tilde{I}}\left[\sum_{j=1}^{3}\theta_j\mathrm{p}(i\in\tilde{I}|j)\right]^{1(i\notin U)}\cdot[\mathrm{p}(i\in\tilde{I}|i\in U)]^{1(i\in U)}\end{aligned}$$

However, because the out-of-pocket responsibility of an insured individual who seeks treatment at least once during the episode is observed, this information should be incorporated in estimation. The likelihood function becomes

$$\begin{aligned}&\mathscr{L}(\Theta,\theta)\\&=\prod_{i\in\bar{I}}\left\{\left[\theta_j\left(\left(\sum_{e=0}^{\bar{E}}\mathrm{p}(e^{f_i}=e\cup N^{f_i}=0|j)\right)\sum_{k=1}^{K}\nu_k\pi^S(k)\mathrm{p}(b_i|j,k)\right)\right]^{1(i\notin U,\ j\ \text{observed})}\right.\\&\quad\cdot\left[\sum_{j=1}^{3}\theta_j\left(\left(\sum_{e=0}^{\bar{E}}\mathrm{p}(e^{f_i}=e\cup N^{f_i}=0|j)\right)\sum_{k=1}^{K}\nu_k\pi^S(k)\mathrm{p}(b_i|j,k)\right)\right]^{1(i\notin U,\ j\ \text{unobserved})}\\&\quad\left.\cdot\left[\left(\sum_{e=0}^{\bar{E}}(\mathrm{p}(E^{f_i}=e\cup N^{f_i}=0|i\in U))\sum_{k=1}^{K}\nu_k\pi^S(k)\mathrm{p}(b_i|i\in U,k)\right)\right]^{1(i\in U)}\right\}\\&\quad\cdot\prod_{i\in\tilde{I}}\left[\sum_{j=1}^{3}\theta_j\mathrm{p}(i\in\tilde{I}|j)\right]^{1(i\notin U)}\cdot[\mathrm{p}(i\in\tilde{I}|i\in U)]^{1(i\in U)}.\end{aligned}$$

The probability of a particular out-of-pocket responsibility for those who are uninsured, θ, is allowed to vary by health status. While the health insurance decision is not modeled, this feature should capture any adverse selection correlated with health status.

TABLE C.I

COMPARISONS OF PREDICTED BEHAVIOR ACROSS MODELS

Outcome	Actual Behavior			Behavioral Model			Reduced Form Model 1			Reduced Form Model 2		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
$p(e>0)$	0.19	0	1	0.19	0.07	0.26	0.19	0.06	0.27	0.19	0.06	0.27
$E(T\|e>0)$	7.35	1	21	7.93	3.08	8.98	7.35	6.90	9.03	7.35	6.51	9.32
$p(v>0)$				0.08	0	1	0.08	0.04	0.13			
$p(v>0\|e>0)$	0.44	0	1	0.47	0.02	0.81				0.44	0.35	0.67
$E(v\|e>0)$	0.49	0	4	0.52	0.02	0.84				0.49	0.33	0.76
$E(v\|v>0)^*$	1.13	1	4	1.10	1.00	1.19	1.12	0.94	1.29			
$p(a>0)$	0.14	0	1				0.14	0.04	0.21			
$p(a>0\|e>0)$	0.74	0	1	0.77	0.34	1.00				0.74	0.57	0.87
$E(a\|e>0)$	1.41	0	12	1.45	0.40	2.99				1.41	1.01	2.10
$E(a\|a>0)^*$	1.90	1	12	1.88	1.13	3.07	1.91	1.49	2.82			

Note: An asterisk (*) implies that the probabilities are conditional on having at least one illness (implicitly) since any medical care visit or absence is associated with an illness. Only the probabilities or averages that are estimated outcomes of each model are listed in this table. Tables C.II and C.III report the derived probabilities or averages of all conditional and unconditional outcomes of interest.

TABLE C.II

MODEL COMPARISONS OF ILLNESS BEHAVIOR

	$p(e>0)$	$E(e\|e>0)$
Baseline		
BM	0.19	7.93
RF1	0.19	7.35
RF2	0.19	7.35
	Percentage Change from Base:	
Experiment	$p(e>0)$	$E(e\|e>0)$
Experiment 1		
BM	3.66	−0.02
RF1	3.78	−0.40
RF2	3.78	−0.33
Experiment 2		
BM	12.72	−1.23
RF1	9.06	−0.92
RF2	9.06	−0.94
Experiment 3		
BM	−23.08	4.43
RF1		
RF2		

Note: BM is behavioral model, RF1 is reduced form model 1, and RF2 is reduced form model 2.

TABLE C.III

MODEL COMPARISONS OF TREATMENT AND ABSENCE BEHAVIOR

	$p(v>0)$	$p(v>0 \mid e>0)$	$E(v)$	$E(v \mid e>0)$	$E(v \mid v>0)$	$p(a>0)$	$p(a>0 \mid e>0)$	$E(a)$	$E(a \mid e>0)$	$E(a \mid >0)$
Baseline										
BM	0.09	0.47	0.10	0.52	1.10	0.15	0.77	0.28	1.45	1.88
RF1	0.08	0.44	0.09	0.50	1.13	0.14	0.74	0.27	1.41	1.90
RF2	0.08	0.44	0.09	0.50	1.13	0.14	0.74	0.27	1.41	1.90
	Percentage Change from Base:									
Experiment	$p(v>0)$	$p(v>0 \mid e>0)$	$E(v)$	$E(v \mid e>0)$	$E(v \mid v>0)$	$p(a>0)$	$p(a>0 \mid e>0)$	$E(a)$	$E(a \mid e>0)$	$E(a \mid >0)$
Experiment 1										
BM	12.73	8.75	15.58	11.50	1.54	−6.16	−9.47	1.90	−1.70	1.14
RF1	1.29	−2.39	1.68	−2.02	0.39	4.45	0.64	5.19	1.37	0.47
RF2	1.42	−2.27	1.66	−2.00	0.17	4.36	0.56	4.71	0.83	0.25
Experiment 2										
BM	16.10	3.00	19.00	5.57	2.13	27.45	13.07	24.66	10.59	6.47
RF1	4.07	−4.58	0.95	−7.44	−2.85	11.26	2.01	11.03	1.81	−0.55
RF2	4.17	−4.48	1.00	−6.85	−2.53	11.16	1.93	13.04	3.23	1.22
Experiment 3										
BM	−47.83	−32.17	−52.48	−38.22	−3.38	−2.10	27.27	−27.76	−6.08	−13.10
RF1										
RF2										

Note: BM is behavioral model, RF1 is reduced form model 1, and RF2 is reduced form model 2.

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